The AIR Professional File

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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

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PREFACE

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

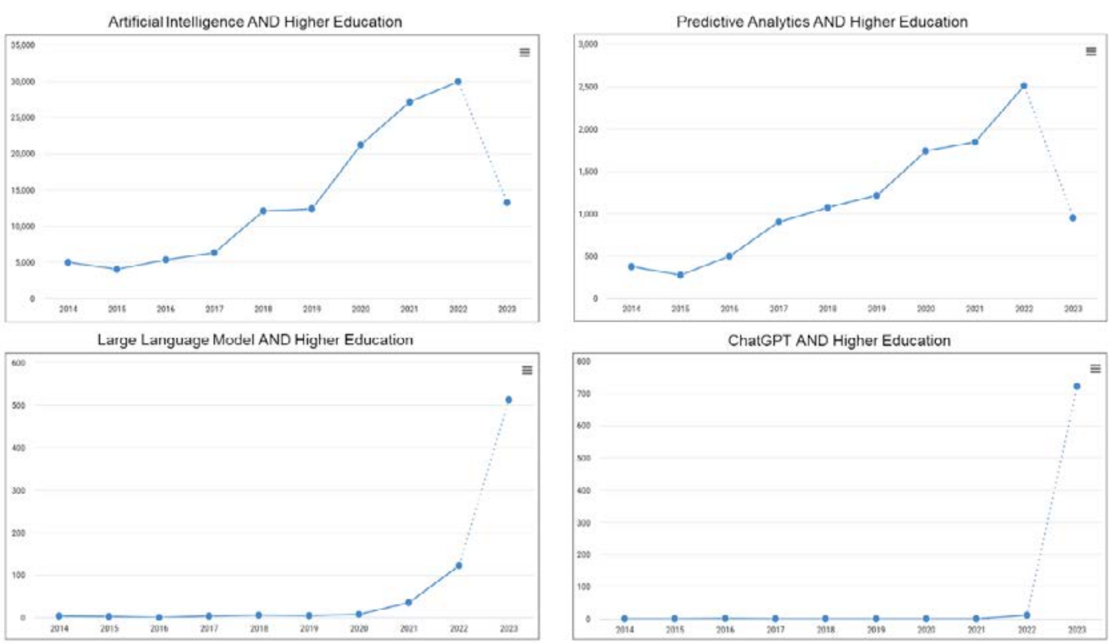
New technologies in our post-pandemic world have prompted substantial changes in every facet of higher education. The emergence of Big Data is one of several key facilitating conditions that accelerated the adoption of artificial intelligence (AI) and machine learning (ML) in key application areas. According 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.

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

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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.

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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.

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Centering Student Voice in Developing Learning Analytics and Artificial Intelligence–Embedded Supports

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Abstract

Accelerating advancements in learning analytics and artificial intelligence (AI) offers unprecedented opportunities for improving educational experiences. Without including students' perspectives, however, there is a potential for these advancements to inadvertently marginalize or harm the very individuals these technologies aim to support. This article underscores the risks associated with sidelining student voices in decision-making processes related to their data usage. By grounding data use within a social justice framework, we advocate for a more equitable and holistic approach. Drawing on previous research as well as insights we have gathered from a student panel, we outline effective methods to integrate student voices. We conclude by emphasizing the long-term implications for the institutional research field, arguing for a shift toward more inclusive and student-centric practices in the realm of learning analytics and AI-embedded supports.

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INTRODUCTION: ADVANCEMENTS IN ANALYTICS AND ARTIFICIAL INTELLIGENCE

Institutional research (IR) professionals have become increasingly central to college and university efforts to improve student success through the use of empirical research and reporting. This tradition goes back to the early 20th century when information technologies and statistical methods were relatively cumbersome, through the information technology explosion of the late 20th century when tools like personal computers, spreadsheets, and statistical packages allowed for more-rapid deployment of research results. The 20-plus years since the beginning of the new millennium have seen another explosion of capacity, with institutional data supplemented by diffuse information systems available from national data systems that can be used for benchmarking and tracking students from their early school years, through college, and into the workforce. Officials at many colleges and universities have had great success leveraging such data systems, as countless sessions at the annual Association for Institutional Research (AIR) Forum have demonstrated.

Recent advances in predictive analytics have opened new possibilities in providing direct support to students—to the instructors who teach them, to the advisors who support them, and to many other new types of professionals that have roles in helping students navigate the increasingly complicated choices available to them within a particular institution and across the higher education landscape. Artificial intelligence (AI) now offers a quantum leap in capabilities that students, faculty, and staff can leverage to support student learning and success. However, there is much peril along with the promise of these technologies: instructors cannot easily tell whether the work submitted by students represents solely their own thinking or if it was aided by AI. It has been demonstrated, too, that AI can contribute to widening equity gaps due to bias inherent in algorithms as well as to equity gaps in access to and use of this powerful technology (Ahn, 2022; Alonso et al., 2020).

While some tremendous successes have already been realized, there are incalculable opportunities still to be discovered. Critical to the discovery of those opportunities is ensuring the involvement of the voice of our most important population: students. An oft-cited achievement in the use of institutional data is Georgia State University's (GSU) predictive analytics service. Since partnering with EAB in 2012, GSU has seen its graduation rates increase by more than 35 percentage points; as of 2023 those rates have been consistent across racial and ethnic lines for 7 years. The institution has increased degrees awarded by 84% and more than doubled the number awarded to low-income and minority students. Powering their alerts are 10 years of data that were reviewed to identify 800 factors that correlate with challenges completing their degrees on time (Calhoun-Brown, 2023). Of equal importance, 42 advisors were hired alongside the service's launch, enabling more advisor–student interactions (Kurzweil & Wu, 2015). GSU has profoundly and positively impacted its students' paths to success, as have many other institutions, aided by the use of advanced information and analytic capacities.

But, as noted, GSU's successes involved more than just leveraging new analytic technologies. The institution was already seeing consistent improvements in its graduation rates before the implementation of its advising alert system in 2012

(GSU, 2021). In their 2015 case study, Kurzweil & Wu (2015) noted that GSU's incredible results are not related to a single solution, but rather to the institution's overall approach to problem solving. Staff members at GSU use the institution's data warehouse to find barriers to graduation and resolve those barriers through a cycle of implementing interventions to remove identified barriers; they assess their effectiveness and scale them up if they find them to be effective. As Kurzweil & Wu (2015, p. 18) note, "It is the process, and not merely its outputs, that other institutions should seek to replicate."

GSU's process included opportunities for centering the student voice. In this article we first describe considerations and risks when student voices are not included in deciding how their data will be used. Next, we discuss ways to ground data use in a social justice framework. Finally, we share perspectives and recommendations on how to support students' successes.

Although applications of AI often operate on a more diverse range of data types and use techniques that are different from predictive analytics, the issues considered in this article apply equally, if not more strongly, given that that the user of AI's output is even farther removed from the analysis process than is the user of predictive analytics.

Considerations and Risks When Student Voices Are Not Included

Understanding that there are risks when students, especially students from marginalized populations, are not involved in uses of their data is critical to avoiding those risks. Fortunately, many lessons have already been learned regarding a lack of participation in data use generally that institutional researchers can consider in the context of their work as they move forward in deploying AI as part of their information use strategies.

First, concerns have been raised among scholars and practitioners working toward data justice that data reflect social ideas of the default as implicitly defined by those with power in a particular context: White, heterosexual, cisgender, abled, neurotypical, financially comfortable, and so on (Benjamin, 2019; D'Ignazio & Klein, 2020). When data are captured, structured, interpreted, and applied on the assumption of a particular default, those who fall outside of that category are less likely to benefit and more likely to possibly experience harm.

Consider AI researcher, artist, and advocate Joy Buolamwini's now-famous experience discovering bias in facial analysis software (Kantayya, 2020). While interacting with the software, Buolamwini found that the software was unable to identify her darker-skinned face (a label that itself implies a default), despite successfully capturing her lighter-skinned colleagues' faces. The software was similarly able to identify the features of a plain white mask she placed over her own face (Kantayya, 2020). Buolamwini and computer scientist Timnit Gebru had previously found that multiple data sets used to train facial recognition software had included majority lighter-skinned subjects, causing the software to frequently misclassify darker-skinned faces, with the greatest number of errors occurring when the software attempted to analyze the faces of darker-skinned women (Buolamwini & Gebru, 2018). These issues of bias and unfairness occur with generative AI, such as Chat Generative Pre-trained Transformer (ChatGPT), as well, and thus require training users on diverse data, careful monitoring, and other bias mitigation tactics (Kasneci et al., 2023). Mitigation strategies should be defined in use policies informed by impacted populations (i.e., students of various identities) to surface issues that others outside those populations may not be aware of. As institutions invest in data-powered identity-based outreach, AI video assessment and proctoring, AI-assisted admissions, or staff interview software, and so on, their similar investments in mitigation strategies will only grow in importance.

Early alert systems are a useful tool for demonstrating the practical risks when services do not incorporate student-guided use policy. Early alert systems are frequently implemented in higher education in an effort to increase retention (Parnell et al., 2018). These systems use data about students that are based on some predefined metrics to identify when students are at greater risk of incurring negative academic consequences, and send an alert to instructors or academic support staff so that they may intervene as appropriate (Hanover Research, 2014). Interventions might include offering tutoring, having a student meet with an advisor, assigning a mentor, or referring a student to a relevant social service (Ekowo & Palmer, 2017).

Numerous risks arise when a diversity of student voices have not been considered in the development, deployment, and operation of early alert systems. First, the integration of multiple data sets means that a risk label can be made more broadly visible, which creates opportunities for riskiness to be assumed in contexts unrelated to the one that the risk was measured against in the first place (Benjamin, 2019; Prinsloo & Slade, 2016). This is additionally problematic given that student identities and circumstances frequently change: while data about students often tend to be rigid, the realities of their lives are not (Slade & Prinsloo, 2013). Without an opportunity to dispute or otherwise provide narrative context alongside their data, circumstances perceived as negative and permanently recorded by an institution official can follow students throughout their academic careers.

In their review of relevant literature, Braunack-Mayer et al. (2020) found that students have expressed concern across multiple studies about being labeled “at risk”; these authors note that being categorized in certain ways could bias their instructors such that they exclude the categorized students from future academic opportunities. In this way, the label “risky” becomes a quality inherent to a student, detached from its use as a descriptor applied to those who are being failed by a specific process or system. Nopper (2019, p. 170) refers to the “digital profile assessed to make inferences regarding character in terms of credibility, reliability, industriousness, responsibility, morality, and relationship choices” as “digital character” that is used to paternalistically “help” individuals, often without their knowledge or consent. (See also Braunack-Mayer et al., 2020.) This focus on applying interventions based on a student’s digital character situates them as data objects or passive recipients of services rather than as autonomous agents (Kruse & Pongsajapan, 2012; Prinsloo & Slade, 2016; Roberts et al., 2016; Rubel & Jones, 2014). Given that groups of students have also expressed such concerns about threats to their autonomy by these systems themselves, it is critical that they are provided mechanisms for having their voices considered (Roberts et al., 2016). This example is not intended to imply that all early alert systems are problematic—there is evidence that students do consider them beneficial (Atif et al., 2015; Roberts et al., 2016). Rather, the example is used here to illustrate the potential issues that may arise if development of such systems is not aligned with student-informed policies for use.

Grounding Data Use in a Social Justice Framework

To productively address risks like those described, we suggest that higher education officials align their efforts to grow data capacities and use AI-infused solutions with their diversity, equity, and inclusion priorities. This is not a novel approach to data use: the social impacts of mass data use have received increasing attention for more than a decade. In 2012, Facebook gained significant media attention around its nonconsensual research on and manipulation of users' moods; the use of its data by political consulting firm Cambridge Analytica in 2018 helped raise public consciousness about mass data's capabilities and misuses (Meyer, 2014; Zialcita, 2019). Zuboff (2019) described how surveillance capitalism—the widespread collection and commodification of personal data by corporations—poses significant threats to society, privacy, and autonomy. Relatedly, O'Neil (2016) laid out numerous examples of the harm Big Data algorithms can cause across contexts, including their use in college rankings and teacher evaluations, and Wachter-Boettcher (2017) discussed the lack of diversity and inclusivity in the technology industry, leading to sexist, inaccessible, and otherwise biased systems. Additionally, Noble (2018) detailed the ways that search engines reinforce racism, sexism, and other forms of oppression; Benjamin (2019) broadened Noble's work, discussing additional applications of data that cause harm to vulnerable populations, including in AI systems.

Applications of data and the calculations we apply to data (i.e., algorithms) have been investigated from a variety of perspectives and within numerous contexts. Out of these investigations has developed the concept of data justice—a framework for engaging with the ways datafication and society intersect with an explicit social justice focus. While there are diverse approaches to and definitions of data justice, there are some themes, including the recommendation to meaningfully collaborate with the individuals whose data will be captured and used during the conception, development, and implementation of data-based systems and the policies governing them (Dencik et al., 2019; Dencik & Sanchez-Monedero, 2022). In academia, these individuals are often our students.

In the remainder of this article, we consider the implications of using a social justice framework for advancing the use of generative AI and other Big Data applications within higher education institutions. This framework derives from a focus on minoritized populations, such as Indigenous peoples and other racial/ethnic minorities, who are often underrepresented within postsecondary institutions. We believe, however, that the ideas pertain more generally to students who, although often the largest group of constituents of a college or university, are not consulted about the use of their personal data within such applications.

PERSPECTIVES AND RECOMMENDATIONS

Numerous communities have shared their perspectives on and recommendations for data use as it relates to their unique experiences. While these communities are not monolithic, the concerns they raise reflect themes that might otherwise go unidentified by those who develop and deploy AI and Big Data applications (D'Ignazio & Klein, 2020).

One such group advocating for data justice is the Native Nations Institute (NNI). The NNI defines a Native nation's data as "any facts, knowledge, or information about the nation and about its citizens, lands, resources, programs, and communities. Information ranging from demographic profiles to educational attainment rates, maps of sacred lands, songs, and social media activities are all data" (Rainie et al., 2017, p. 1). The NNI aims to promote Indigenous data sovereignty using the CARE Principles for Indigenous Data Governance that were developed by the Research Data Alliance's International Indigenous Data Sovereignty Interest Group in 2018 and published in 2020 (Carroll et al., 2020). The CARE Principles and their subcomponents are summarized in Table 1.

Table 1. The CARE Principles for Indigenous Data Governance

Principle	Component
Collective Benefit	For inclusive development and innovation For improved governance and citizen engagemen For equitable outcomes
Authority to Control	Recognizing rights and interests Data for governance Governance of data
Responsibility	For positive relationships For expanding capability and capacity For Indigenous languages and worldviews
Ethics	For minimizing harm and maximizing benefits For justice For future use

Source: Adapted from Carroll et al., 2020, Figure 2.

The Responsibility principle's first subsection, "For positive relationships," identifies that "Indigenous data use is unviable unless linked to relationships built on respect, reciprocity, trust, and mutual understanding, as defined by the Indigenous Peoples to whom those data relate" (Carroll et al., 2022, p. 4). The following subsections, "For Expanding Capability and Capacity" and "For Indigenous Languages and Worldviews," require efforts to increase data literacy and to ground data in the world views and the lived experiences of Indigenous peoples, respectively. Each of these subsections implies some form of collaboration between institution officials using Indigenous students' data and the students themselves: to create mutual understanding, to increase data literacy between both parties, and to enable Indigenous students to (consensually) share their experiences.

When considering the use of early alert systems, it is important to note that the CARE Principles for Indigenous Data Governance specify that ethical data not portray Indigenous peoples in terms of deficit, and that benefits and harms should be evaluated from the perspective of the Indigenous peoples the data relate to (Carroll et al., 2020). This guidance provides a model for data use policy development that may be applied to other student populations regardless of identity; rather than administrators determining what may harm or benefit communities, administrators can consult with those communities to provide their contextualized view of potential risks and benefits, and to describe assets to highlight with students.

Although designed with specific focus on a highly marginalized population, the principles can be applied more generally to incorporating student voice into the formulation of machine learning (ML), AI, and other Big Data applications and resources. However, these principles also remind us that we need to pay special attention to the voices of marginalized student populations, such as racially minoritized students and other subgroups that are not well represented by the dominant student culture.

Other issues related to data capture have been identified as well. Ruberg & Ruelos (2020) note that it is difficult to accurately represent gender and sexuality using traditional demographic capture-and-reporting techniques. Those authors provide multiple recommendations based on their findings: (1) When capturing gender and sexuality, multiple answer possibilities should be available. (2) Gender and sexuality identities may change, and all reported identities are valid unless the individual states otherwise. (3) Collaboration with relevant communities is critical for understanding and accurately capturing their identities.

Finally, marginalized groups are often centered and surveilled by both punitive and purportedly supportive systems, which promotes feelings of threatening hypervisibility (Benjamin, 2019). Asher et al.'s (2022) survey of student perspectives on library analytics found that students in minority racial/ethnic groups and those of lower socioeconomic status were more concerned than the overall student population about the privacy of their personal data, thus supporting this perspective in the academic context (Asher et al., 2022). Collaborating with students, especially those who experience heightened surveillance, may help to shift support methods such that students experience them in a less threatening manner. To this point, GSU's predictive advising service provides another example: risk factors are shared with students as well as with advisors, promoting transparent conversations; and advisors are thoroughly trained on how to use the service as well as how to have discussions about its outputs with students (Bailey et al., 2019).

Methods for Including Student Voices

There are a variety of potential methods for involving student perspectives when developing access and use policies. West et al. (2020) note that these methods could include research into students' descriptions of their own needs, concerns, and ideas for how learning analytics might benefit them, as well as the creation of user users' stories and principles against which data-based tools may be built. Jones et al. (2019, 2020, 2023) demonstrate adaptable methods for gathering student feedback in their studies by collecting student perspectives in three phases across 3 years: first, they conduct interviews with undergraduate students across eight U.S. institutions, then they send a quantitative survey to random samples of students across the same eight institutions, and finally they hold virtual focus groups centered on discussions of data use scenarios rooted in real-life practice. Data for Black Lives' report, *Data Capitalism + Algorithmic Racism* (Milner & Traub, 2021), suggests a few methods for supporting collective data practice that can be adjusted for the higher education context, such as Collington's (2019) proposed "system including a digital platform for debating and deciding priorities for use of public data" (Milner & Traub, 2021, p. 26).

An even more-robust strategy is provided in *A Toolkit for Centering Racial Equity Throughout Data Integration from Actionable Intelligence for Social Policy*, which includes guidance for involving community voices at every stage of design, use, and implementation of data-infused practices (Hawn Nelson et al., 2020). While the *Toolkit* was developed to support those using data for civic purposes, many of its recommendations apply to higher education data uses and align with calls from the learning analytics field to include student voices at all levels of data use, from design development through membership in oversight committees (Braunack-Mayer et al., 2020). Among other recommendations, the *Toolkit* suggests involving diverse community members in discussions about algorithms and their purposes early in the design stage, inviting people with multiple perspectives to provide potential interpretations of data that will be used.

Using a Student Panel Methodology to Center Student Voice

A method that incorporated both surveys and focus groups was devised as part of a university-wide student success initiative within the authors' institution. Fifteen students were initially recruited from across the institution's seven campuses, and most of the same students attended each panel, which helped to establish an environment of open sharing. For the panel exploring student views on the use of learning analytics and Big Data, the student panelists first reviewed a set of materials related to the use of learning analytics at several different universities, as well as among a community of learning management system users. Students then completed a survey including questions about their awareness of the types of data collected, about their privacy and agency regarding learning data, about issues related to instructors and advisors who have access to and use the data, as well as questions about the benefits and risks with the use of these data. Student responses were split somewhat evenly on the awareness of the types of data that were being collected, but the majority (70%) of the students disagreed with the statement that they were adequately informed about how their data were being used. Interestingly, while more than 80% of the students agreed that there are benefits to making these data available to their instructors, 40% agreed with the reverse statement that such awareness may also negatively impact their motivation and engagement in a course.

The panel discussion focused on four questions for which the students used Google's Jamboard app to record and organize their ideas into themes. The four questions asked were the following:

1. What were your reactions to learning about the kind of learning data that your instructors can access?
2. What were your reactions to advisors' use of Early Alert Systems?
3. How do you feel about your learning data being used to identify that you are struggling in a course?
4. What would you like your instructor to communicate to you about learning data use in your courses?

After completing the analysis, the students were split into two groups to formulate a plan or list of recommendations regarding safeguards/procedures that should be in place to ensure that inequities or biases are not introduced in the use of learning data in a course. Table 2 shows an organization of the thematic responses to this task from the student panelists.

Table 2. Thematic Responses from the Breakout Room Activity During the Panel

Themes	Examples/Explanations
Possible forms of biases in current practices	• Instructor shows favoritism for students struggling less. • Not all struggling students receive the appropriate outreach. • There are biases regarding students' socioeconomic status backgrounds. • Student backgrounds (e.g., they were homeschooled, are first-generation students) lead to different knowledge or resources used to reach out to students with invisible needs.
Theme 1 **Transparency/Open Communication**	• Student consent should be collected before the data are collected and shared with instructors, advisors, or any other parties. • The types of data collected or shared should be communicated clearly to both students and instructors. • Researchers should explain to the students how the data are being used or will be used. • Students should have access to their own learning data. • All students should have equal access to resources and support.
Theme 2 **Training**	• Instructors, advisors, and anyone who may be in close contact with any student data should receive bias and diversity training. • Instructors and advisors should be trained in how to be sensitive to when and especially how to reach out to struggling students with more care and attention to their words. • Instructors should be trained in how to initiate contact with students.
Theme 3 **Human Oversight**	• There should be a separate office that analyzes student data before the data are used by instructors or advisors for reaching out to students, or by students themselves. • There should be more communications or surveying of students to better understand their perspectives and opinions. • Teachers and administrators or advisors should be allowed to review their decisions based on their bias trainings.

Through the survey responses and the panel discussions, student data use is clearly a topic that is sensitive and requires more attention to its ethics and to the treatment of individuals. When using AI and Big Data in higher education, we must be more diligent in protecting the humans behind the numbers. Students may feel uncomfortable when they become aware of the data that are being collected about them; that sense of discomfort can escalate when the data are shared outside of the context where they are generated, such as in-class data being shared with an academic advisor. Finally, the panel discussion revealed a concern about how students are treated when the data are used: Will they be treated fairly? Is outreach done with sensitivity and care? And how can marginalization and biases be avoided in terms of access to resources and support?

This student panel methodology serves to center student voice in IR and to inform policies. To accurately represent students' voices, however, it is essential to reflect the diversity of the student body to avoid bias. For example, while this student panel was recruited from various campuses of the same institution, more than half of the student panelists were from the main campus. Even though this accurately reflects the representation of students across the university, it skews the possible viewpoints and practices experienced by the students. Similarly, their classification (year), gender, race/ethnicity, socioeconomic status, and other demographics should also be taken into consideration when recruiting to prevent representation disparity in data that could lead to unjust applications, such as Buolamwini's facial analysis software, as mentioned before (Buolamwini & Gebru, 2018).

THE IMPORTANCE OF BRINGING IN STUDENT VOICES AND IMPLICATIONS FOR THE INSTITUTIONAL RESEARCH FIELD

Actionable Intelligence for Social Policy's *Toolkit* (Hawn Nelson et al., 2020), discussed earlier, recommends questioning how data use can help communities (i.e., students, in our context) to interrogate systems, as opposed to using data only to identify how to treat those communities. To align with effective and ethical practice, we recommend that institutional researchers intentionally and continually frame their work as student-centric as opposed to intervention-centric, and that they direct their actions in response to collaborations with students primarily toward the systems the students interact with instead of the students themselves (Hawn Nelson et al., 2020; Kruse & Pongsajapan, 2012; Slade & Prinsloo, 2013). Actionable Intelligence for Social Policy's *Toolkit* (Hawn Nelson et al., 2020) includes activities that may be adapted for this purpose. Practical steps for operationalizing racial equity in data use are included, as well as numerous real-world examples of the guidance in practice. Once again, GSU's approach to data use in support of student success provides an example of this practice in action: by asking first whether the institution is the problem (i.e., by interrogating the institution's systems), GSU has been able to find and resolve significant barriers facing students (Kurzweil & Wu, 2015; Zipper, 2022). It is crucial to involve student voices: in addition to data, students can provide context for *why* something was a barrier as well as advice for how institutions can break down barriers.

It is critical that student voices are actively centered when developing data access and use policies. When we authentically include student voices in the development of data policy, we can uncover novel opportunities that will be situated in the contexts of our most important constituents. We can learn what they value and what their challenges are from their own perspectives instead of mediated, decontextualized data sets. Including students in the development of data policy and system development increases trust, and fosters development of systems and initiatives that support success as students define it. In this article, we have shared one approach used for our context and numerous other approaches that could be adapted, and we invite institutional researchers to consider how they may take advantage of these methods for their contexts as well.

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Advising at Scale: Automated Guidance of the Role Players Influencing Student Success

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Abstract

Although student advising is known to improve student success, its application is often inadequate in institutions that are resource constrained. Given recent advances in large language models (LLMs) such as Chat Generative Pre-trained Transformer (ChatGPT), automated approaches such as the AutoScholar Advisor system affords viable alternatives to conventional modes of advising at scale. This article focuses on the AutoScholar Advisor system, a system that continuously analyzes data using modern methods from the fields of artificial intelligence (AI), data science, and statistics. The system connects to institutional records, evaluates a student's progression, and generates advice accordingly. In addition to serving large numbers of students, the term "advising at scale" refers to the various role players: the executives (whole-institution level), academic program managers (faculty and discipline levels), student advisors (faculty level), lecturers (class level), and, of course, the students (student level). The form of advising may also evolve to include gamification elements such as points, badges, and leaderboards to promote student activity levels. Case studies for the integration with academic study content in the form of learning pathways are presented. We therefore conclude with the proposition that the optimal approach to advising is a hybrid between human intervention and automation, where the automation augments human judgment.

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INTRODUCTION

Traditional academic advising in a one-advisor-to-one student approach is resource intensive and difficult to sustain, prompting institution officials to develop alternative student advising models (Thiry & Laursen, 2011). This approach uses analytics to sort students by their likelihood to drop out or stop out, which allows advisors to prioritize their time in favor of students that face rising risk. Networks of advisors, faculty, and other student support leaders form teams that can effectively address the complex needs of students. This approach allows for efficient use of resources and a focus on individualized academic advising (EAB, 2023).

Although institution officials continue to offer ongoing support programs such as orientations, tutoring, and learning centers (Bornschlegl et al., 2020), such resources typically require students to actively seek out those programs (Fong, 2021). Many universities struggle to develop and maintain effective advising services that promote student satisfaction and increase student retention (Anderson et al., 2014). In response, there has been an ascendancy of automated advising approaches to mediate the challenges of diminishing resources and the perceived lack of value in the conventional approaches for advising (Atalla et al., 2023; Rawatlal, 2022).

In the South African context, academic advising provides structured support by an institutional advisor to a student. The resources necessary to provide such a facility, however, may limit the number of students who can receive such advice. Kuhn (2008, chap. 1) describes various models of academic advising. The nature of the advising could be to inform, suggest, counsel, discipline, coach, mentor and even teach. The practice helps students align their various goals through a continuous developmental process to promote their own success. The act of academic advising lies on an advising–teaching and an advising–counseling spectrum.

Evidence of the positive role by student advisors in student success has been mounting, warranting institutions to formalize and professionalize academic advising. In South Africa, advising is being professionalized through the coordinated efforts of ELETSA, which translates to the word “advising” in Sesotho, which is one of South Africa’s 11 official languages. ELETSA is a South African nonprofit organization that seeks to provide leadership in cultivating collaborations across institutions in the area of academic advising. The association holds allied membership status through the Global Community for Academic Advising (NACADA), which is based in Kansas.

ADVISING AT SCALE

Although wide-scale student advising is thought to significantly improve the graduation rates, traditional forms of advising are relatively resource intensive. While automation and web-based systems are obvious candidates to scale the advising, such systems must offer a high enough level of customization to be effective in the context of a diverse student body. In particular, the operation of such systems should acknowledge a constantly iterative development approach as the needs change in response to the effectiveness or lack thereof of the approaches of the previous iteration.

Advising as a High-Impact Practice

As the practice of academic advising intensifies across institutions, it is being portrayed as a social justice imperative for higher education, and potentially as a high-impact practice (Keup & Young, 2021). However, advising large numbers of students requires substantial investment that challenges under-resourced institutions (Assiri et al., 2020). One-on-one advising approaches alone are therefore neither feasible nor effective, and motivate the inception of automated systems that might minimize incorrect advice and the load on academic advisors (Assiri et al., 2020).

Evidence is now also emerging on the nonacademic or quasi-academic benefits of advising (Haley, 2016). Using expectancy violations theory as a lens, Anderson et al. (2014) argue that student satisfaction with advising is linked to alignment between student expectations of the advising process and perceived advisor behaviors. In some instances, student queries are merely information seeking, such as when they ask for schedules and timetables, financial aid sources, and other pragmatic needs. This is evidenced in the application of chatbots to automate this brokering and to ensure more-effective use of a human advisor's time.

Automated Advising

Recent developments in AI have resulted in the emergence of chatbots in higher education to automate specific student queries for information brokering, thus freeing human advisors to focus on more-complex tasks (Meotti, 2023). AdmitHub, an AI developer, has partnered with more than 100 universities to improve student access and retention by using chatbots (Page & Gehlbach, 2017). Bots of this type use natural language processing to support student success (Chen et al., 2023).

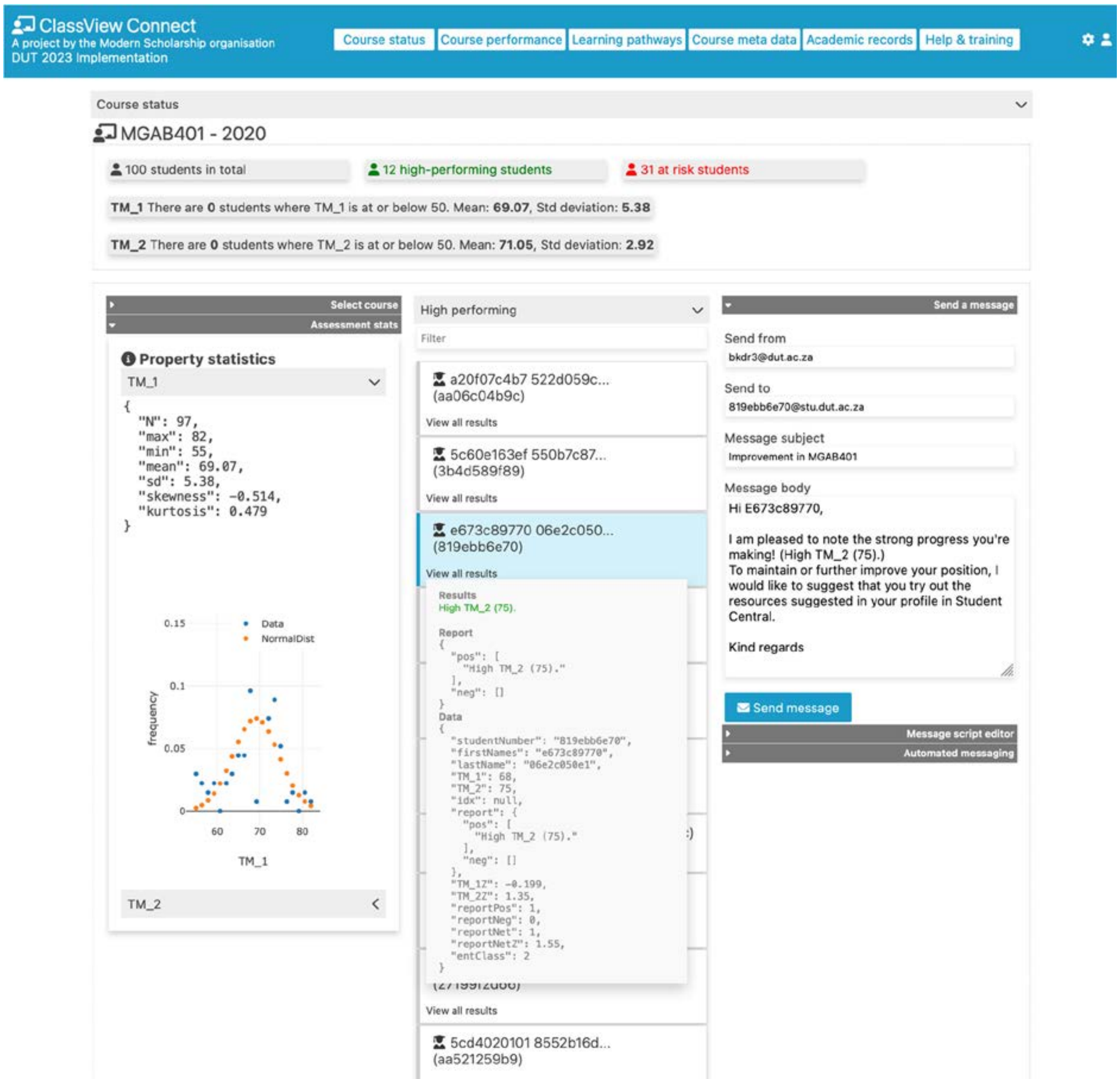
At Georgia State University (GSU), a chatbot helps students with preenrollment processes such as navigating financial aid (Nurshatayeva et al., 2021); GSU's chatbot has led to significant increases in retention and graduation rates. The chatbot's effectiveness continues after enrollment: research indicates that students who used GSU's chatbot were 3% more likely to re-enroll, while having higher rates of FAFSA filing and registration (Nurshatayeva et al., 2021).

Automated systems can aggregate and process large amounts of data more efficiently than humans. This can lead to more-informed advice, since the system can consider various factors and possibilities (Shift, 2022). In recognition of the various roles that support student success, the AutoScholar Advisor system uses AI to generate advice to the various levels of seniority in the higher education institution to fully support and integrate the various interventions that can lead to increased student success.

Evolutions in Student Advising

When generating automated advice to students, we acknowledge that human motivation is a complex field that requires high variance in responses. The factors that prompt action may differ from context to context or from person to person. When generating advice through the AutoScholar Advisor system, it was therefore necessary to evaluate the advice rendered in a variety of contexts to serve as large a group as possible.

A screenshot from an early instance of student advising is shown in Figure 1.

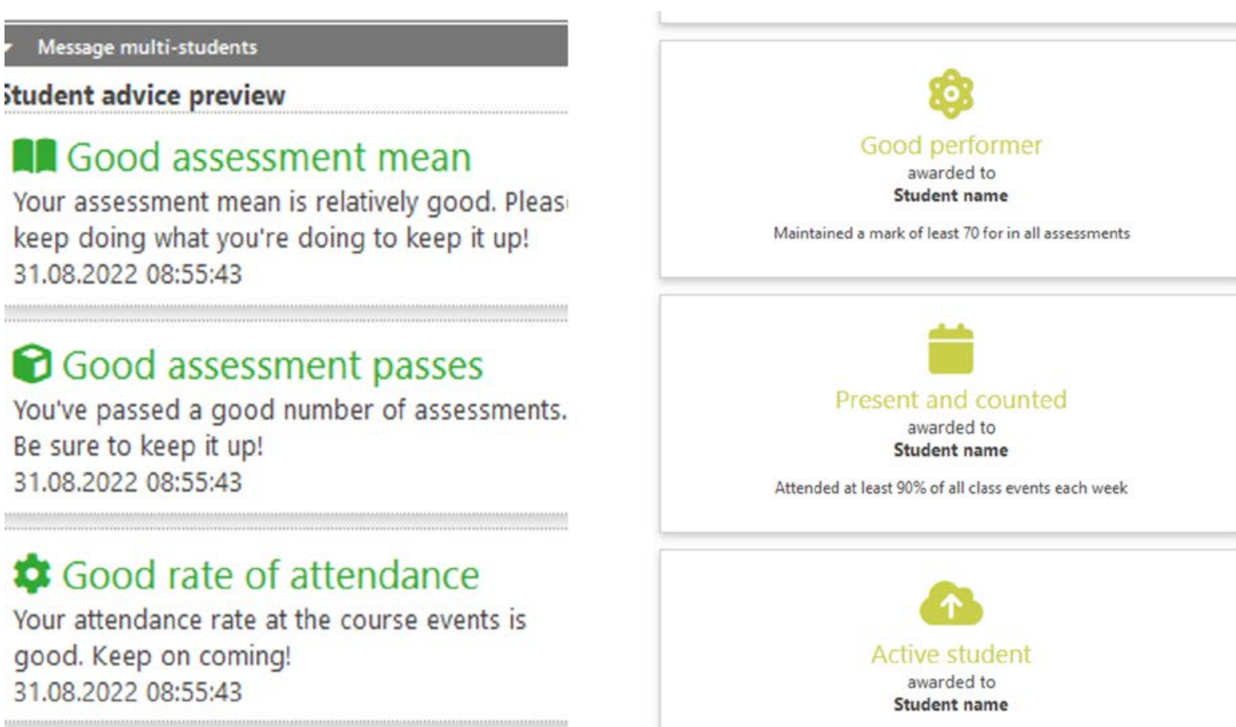


Note: Student numbers and names have been hashed.

In this case, the system calculates the assessment statistics in a class and determines which students are significantly underperforming by computing the number of standard deviations between the mean and each student's result. Based on this value, an apparently personalized message is generated to the student; each message includes some specific data about that student's current and potential future performance. In other words, from a single advising script, which is itself prompted by the student's performance metrics, the system can generate a message to each student that appears to be customized to that student's profile. A default advising script is included that may be further customized by a lecturer or student advisor. The system advises both high-performing students and average-performing students to continue improving and suggests engagement with learning resources available elsewhere in AutoScholar. In the case of underperforming or at-risk students, it further suggests engaging with student support. This form of advising is already a partial evolution; in the first versions, it was possible for the system to alert students of their being at risk of failure. In the version shown in Figure 1, the advice is heavily moderated only to suggest engagement with available services.

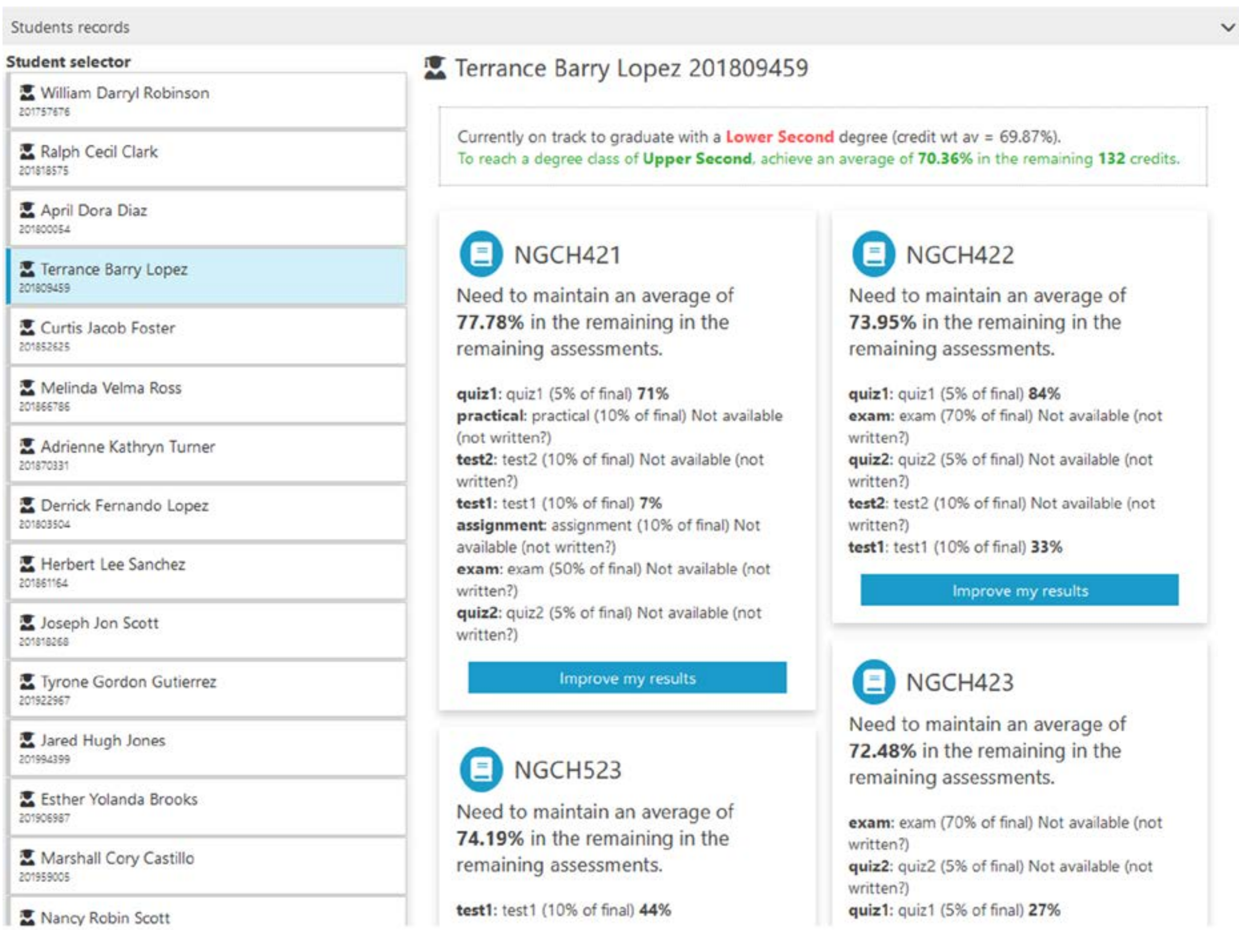
The advising concept may be further generalized to include gamification elements. As shown in Figure 2, the advising may take the form of virtual awards and badges that can be attached to a student's profile. Although these virtual awards require no resources from the institution, they are a powerful means of driving student activity, since students value these awards to a high degree in their applications for scholarships and employment.

Figure 2. Advising in the Form of Virtual Awards



While the application of points, badges, and leaderboards can drive students' level of engagement, one has to apply these methods judiciously to avoid degradation of the educational experience to one of jumping through a series of hoops and thereby limiting the experience of a cohesive curriculum. To develop the sense of an integrated whole, the third evolution of student advising involves providing a large goal to students based on an assumption of a graduation and an assumption that each student is striving not merely to pass, but also to accomplish academic excellence. Figure 3 illustrates this evolution.

Figure 3. Advising for Success ng: The Simulated Case Study



In this case, the system advises students (see top right) of their current status, which, based on their current records, indicates that they are on track to graduate with a lower second class of degree. (For institutions that do not implement such a classification, this can be substituted with mark ranges such as credited weight average in excess of 70%.) The system also alerts students that they can graduate with an upper second class of degree instead by improving their performance by only a few fractions of a percentage point. This provides a student with an overall objective based on an assumption of a final graduation rather than simply the avoidance of failure.

Furthermore, below that top-right box the system shows students which classes they are currently registered for, together with their performance in the various assessments. It notes to students what their minimum performance level should be in the remaining assessments in that class to accomplish the overall goal with respect to the final degree. This evolution of advising can encourage the student to constantly strive higher and achieve a greater level of academic accomplishment.

MULTIDIMENSIONAL ADVISING: ROLE PLAYERS IN HIGHER EDUCATION

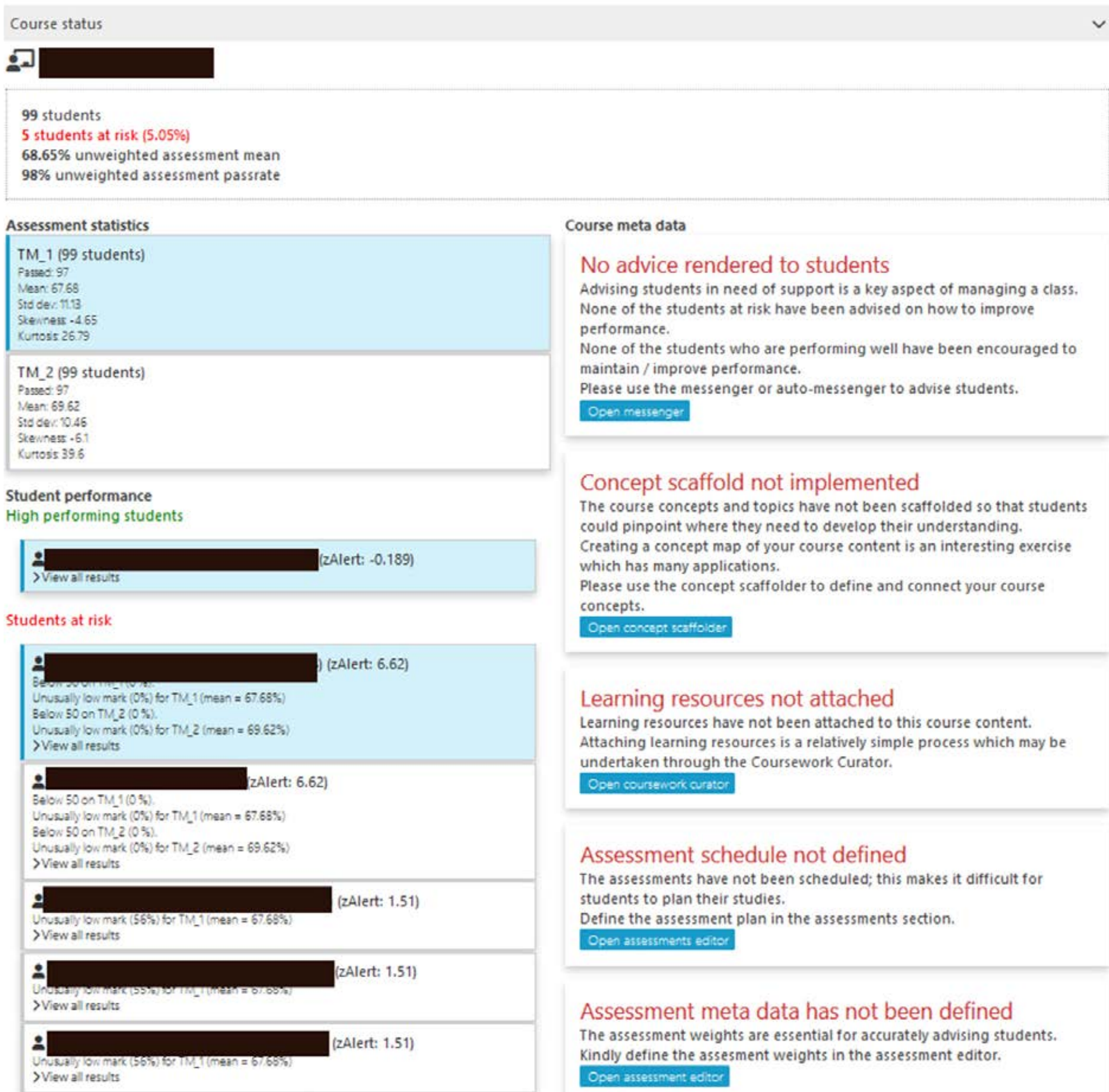
To achieve significant improvements in the progression and hence the graduation rates, it is necessary for the various role players to receive accurate advice. At the student scale, advice on coursework registration as well as day-to-day study habits are a direct influence. Advice to lecturers with respect to students at risk and course management practices can significantly improve the student (and lecturer) experience. At the counselor scale, the ability to benchmark a student against the student population is key. At the executive scale, the allocation of resources to support teaching and learning to specific programs should correlate with the performance levels in the programs.

Role Players in Higher Education: Another Dimension in Advising at Scale

Although advising at-risk students is emphasized at most institutions, it is also necessary to advise the other role players that influence student success. Lecturers require advice on their course/module management, student advisors require insights into student performance to render advice effectively, faculty management require insights into which academic programs require more teaching resources, and executives require insight to the faculties that would benefit from additional financial resources. Some case studies in advising these roles players are shown in Figures 4 through 8.

In Figure 4 it is possible to understand which students require advising as well as to identify the various activities that can be undertaken to better organize the learning content and to generally support better student engagement with the course content.

Figure 4. Screenshot from ClassView Connect Component of the AutoScholar Advisor System



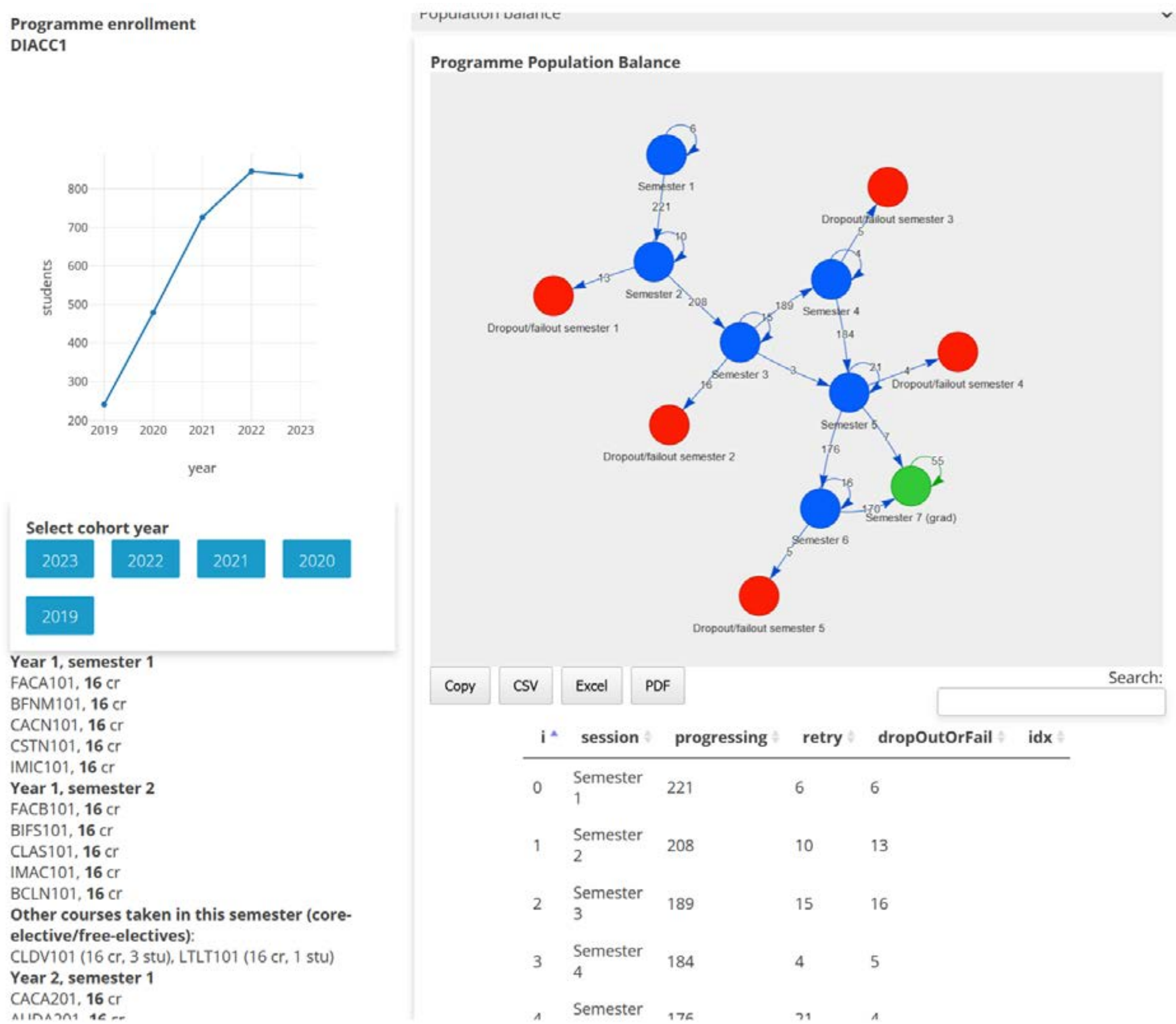
Note: Advice rendered to lecturers to manage classes better.

From the perspective of an academic program manager, such as a head of department or program convenor, it is also useful to identify which coursework in a program should be prioritized to resolve low pass rates. Figure 5 illustrates analysis of an academic program where low pass rates, the influence of a high confluence of prerequisite requirements, and the impact on senior courses; students then take those courses later than intended.

Figure 5. Program Analyst Component of AutoScholar: Identification of Coursework Issues

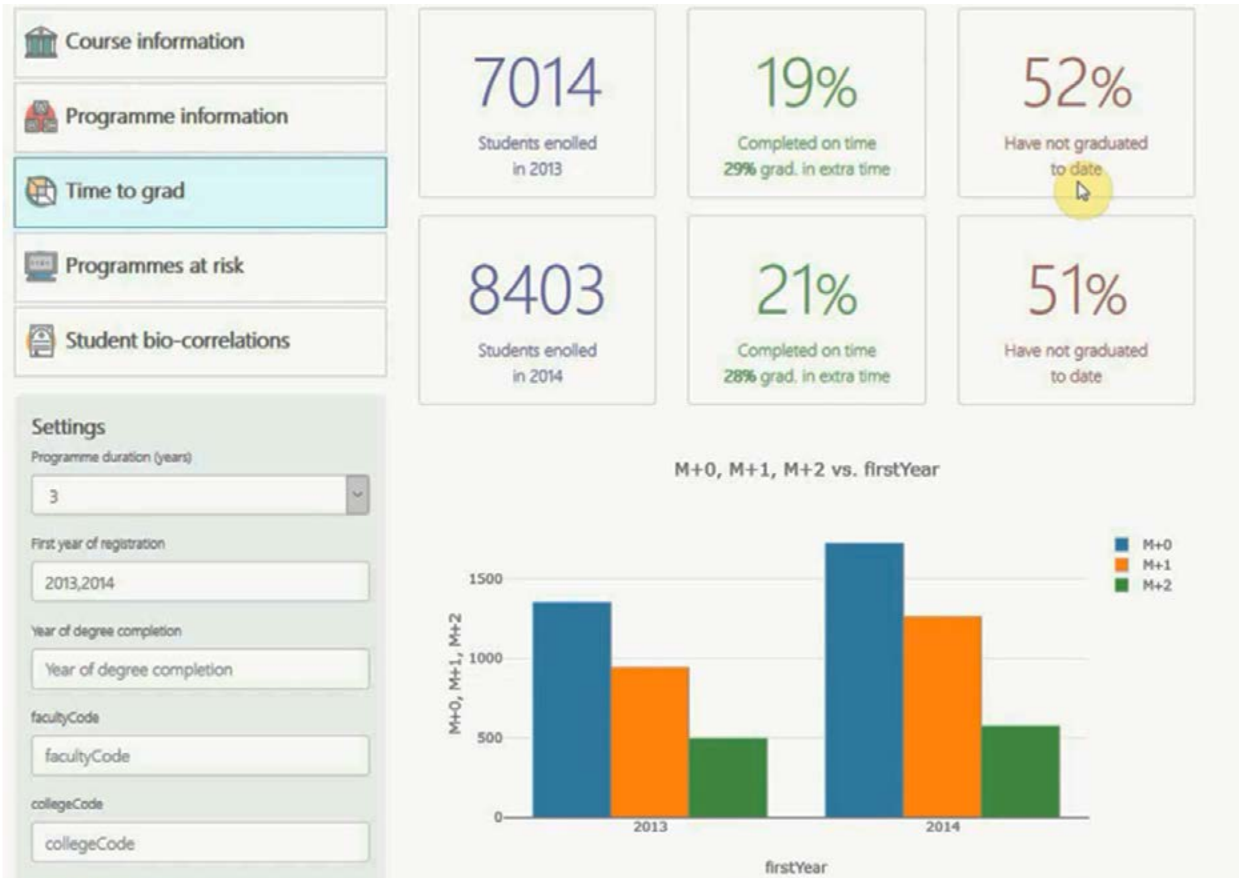
To fully advise faculty staff on student progression, it is also necessary to evaluate the transfer of students from one semester to the next, and to maintain awareness of the various combinations of courses involved in the various routes to graduation. Figure 6 illustrates that a program manage can determine at which point in the curriculum the largest number of students exit or recycle.

Figure 6. Population Balance Illustrating Student Progression through an Academic Program



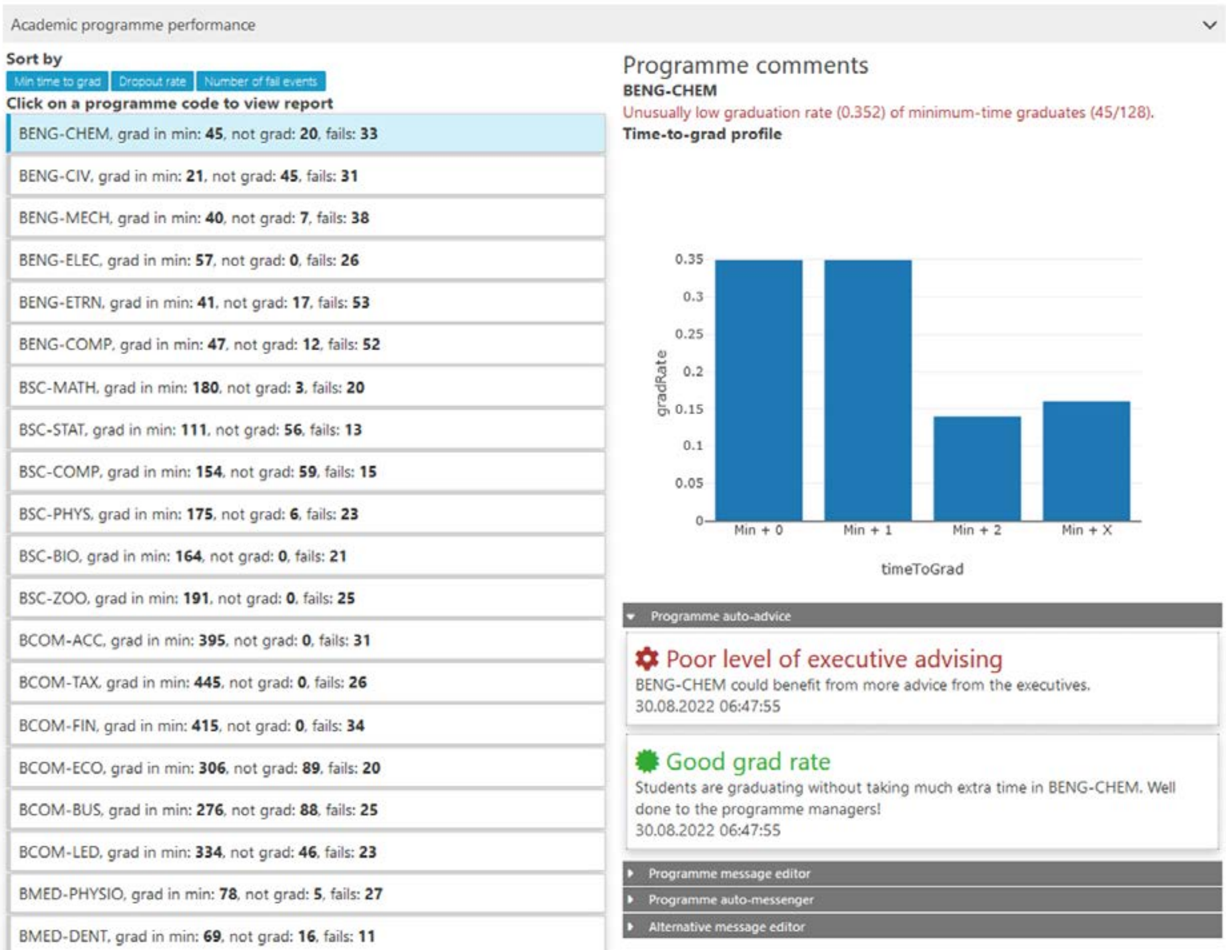
At the whole-institution scale, executives maintain a bird's-eye view of the entry and graduation statistics. In particular, given an entering cohort in a particular year, it is necessary to monitor what fraction of students complete in minimum time and what fraction exit without graduating (Figure 7).

Figure 7. Executive Insight Component of AutoScholar Advisor System to Monitor Institutional Progression



To take action by alerting relevant staff or allocating resources, the next step would be to determine, among all academic programs at the institution, which programs exhibit the lowest pass rates and lowest performance indices. Figure 8 illustrates that such programs can easily be identified.

Figure 8. Executive Insight: Identifying Academic Programs in Need of Support



It is therefore possible for all role players in higher education to receive sufficient insight and hence to apply suitable interventions or allocate resources to ameliorate the limitations identified. Such data-oriented advising may be directly applied in most cases. At the student level, however, it could be more necessary to moderate the advice rendered by interpreting the results and suggesting interventions based on the student temperament and degree of reception to critical feedback.

Hybrid Advising

In academic advising, human advisors often do not have all the requisite information at hand, with inherent limitations in what they can do with such information. For example, an advisor cannot make decisions for an advisee, but can provide various alternatives for the student to consider. Similarly, an advisor cannot increase the native ability of the advisee, but can encourage maximum use of that ability. Advisors also cannot reduce an underperforming student's academic load, but can recommend appropriate interventions. Confidential matters also present challenges, since advisors must balance the need for information exchange with the need to respect student confidentiality. Furthermore, when complex problems arise related to financial aid, mental or physical health, or personal or social counseling, advisors often have to refer students to other professionals.

Given the inherent diversity in student attributes, moderating advice to students is essential as students navigate the complexities of their institutions. Personalized connections can help bridge the gap between expectations and experiences, especially for international students and those who require support to prevent departure before graduation (Moore, 2022).

This points to the value of hybrid advising, which combines in-person and online elements, and can help to mitigate some of these challenges by using chatbots to handle routine transactions while leveraging human interactions to address specific and unique situations. The Covid-19 pandemic accelerated the blending of in-person and online learning in many schools, a shift that, despite its challenges, can potentially enhance the academic experience in the long run. This hybrid model can help break down barriers to access, allowing universities to reach a broader and more diverse population of students. It can also better meet the changing workforce's needs and provide working adults with lifelong learning and career opportunities (Selingo & Clark, 2021).

Implications for Institutional Research

The approaches outlined here emphasize awareness of a need for intervention at a specific point of application. It is also possible to apply this approach to evaluate the effectiveness of any specific interventions that might be applied. Such an approach is typical of Improvement Science frameworks (Perry et al., 2020), where the continuation of an intervention must be evaluated according to the observed improvement or lack thereof. In fact, it is a well-established practice in Improvement Science to reevaluate not only the suitability of any applied interventions, but also the metrics used in the evaluation itself.

It is also worth noting that, although metrics are cited for the performance of students at the whole-institution scale, the system also generates the same statistics at the college, faculty, and academic program levels. This is significant since the context of the student and nature of studies undertaken will influence the performance metrics. It then becomes possible to customize the applied interventions rather than assuming that a blanket strategy applies to all disciplines.

The ease of access to data analysis may also afford new insights to the student support staff. Student advisors often complain that their role devolves to simple information brokering rather than affording students insight to performance improvement. This is at least in part due to nonacademic advising emphasizing the student impression of the severity of the challenges faced. If an advisor is also able to correlate this with actual changes in performance as reflected by data showing a student's progression, it might be possible to review perceived challenges more objectively and hence to raise the value of the advice rendered.

It is still necessary to actively challenge the interpretation of data, however. Various forms of bias easily enter even careful analysis, to say nothing of the tendency to adopt an auto-generated message as the gospel truth. There are as many as six main categories of bias (confirmation, selection, historical, survivorship, availability, and outlier). Without suitable training, it is all too easy for a viewer to take action that yields unexpected results.

On the other hand, it is known that the students most in need of support are often the least likely to ask for it. Automation may play a role in provoking at least a conversation if not an active engagement between a student and a human advisor that might not otherwise have occurred. There are rich possibilities for the hybridization of automated and human advising.

There are other implications for the AutoScholar Advisor system for institutional research (IR) and institutional effectiveness (IE) professionals. It is possible that IR or IE officials can engage in collaborative work with academic advising staff on how data are collected, managed, and prepared for the feedback loops. In addition, the IR analysts might want to design a study to examine student success based on use of the AutoScholar Advisor system (e.g., perhaps a pre–post type of research design). This could yield great benefits for students and provide return-on-investment rationale for use of the system. Other research studies may also be considered, such as the evaluation of different models of advising on student experience and satisfaction: automated, human, and hybrid advising.

IR and IE officials might also want to ensure that other colleagues are considering potential bias that can occur in data (majority vs. minority students, or other known facets of differences). Indeed, we believe that this system can help underserved student populations and that IR officials can help articulate those benefits to campus colleagues.

CONCLUSION

In this article we have attempted to demonstrate that, while academic advising has consistently been rated a top predictor of students' success and satisfaction during their undergraduate careers (Anderson et al., 2014), the traditional human-centered academic advising is a resource-intensive process that is difficult to sustain, prompting institutions to develop alternative advising models. Based on our experiences of advising development at a South African university, we contend that automated systems that use AI techniques (such as the AutoScholar Advisor system) can "minimize incorrect advice, minimize the load on academic advisors, solve the issue of the limited number of advisors, and free up more of their time" (Assiri et al., 2020, p. 1).

However, automated systems alone can have unintended consequences, such as engendering demotivation among students. We therefore conclude with the proposition that the optimal approach to advising is a hybrid between human intervention and automation, where the automation augments human judgment. In this modality, the automated advice function provides the initial prompt to alert students of their at-risk status or of their potential to attain higher grades. These students are then ushered to appropriately qualified advisors who provide the human touch to ameliorate the limitations of automated systems.

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Reflections on the Artificial Intelligence Transformation: Responsible Use and the Role of Institutional Research and Institutional Effectiveness Professionals

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Abstract

This article explores the potential impact of artificial intelligence (AI) and machine learning (ML) on higher education. It overviews current generative AI capabilities and argues for ethical frameworks to address issues such as bias. The article advocates for a multidisciplinary governance approach involving institutional stakeholders by examining past academic technology adoption. It highlights the strategic role institutional research (IR) and institutional effectiveness (IE) professionals can play in navigating AI complexities. This article provides specific suggestions for IR/IE professionals to embrace the role of AI ethicist: continuously developing AI literacy, ensuring ethical deployment, upholding privacy and confidentiality, mitigating bias, enforcing accountability, championing explainable AI, incorporating student perspectives, and developing institutional AI policies. The article concludes by asserting that IR/IE's research expertise, ethical commitment, and belief in human judgment equip the field to adapt to and lead in the AI era. By taking an active role, IR/IE can shape the technology's impact to benefit higher education.

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INTRODUCTION

As discussed in this volume's preface and evidenced by the other articles in this volume, artificial intelligence (AI) and machine learning (ML) are far from new concepts (Stahl, 2021). Until recently, however, discussions around these tools were predominantly confined to specialists, researchers, and enthusiasts. This changed in November of 2022 when Chat Generative Pre-trained Transformer (ChatGPT) provided unprecedented access to this technology, ushering in a new wave of widespread interest. Seemingly overnight, generative AI had catapulted to the forefront of public awareness. AI and ML started to permeate every field and industry, spanning technology, business, health care, law, and education. The reactions ranged from excitement and enthusiasm to criticism and concern. While generative AI has the potential to increase efficiency, encourage exploration, and spark creativity, it also has the potential to disseminate misinformation, compromise privacy, and amplify biases (Megahed et al., 2023; Shahriar & Hayawi, 2023). Certainly, as these technologies continue to evolve, they also continue to introduce opportunities and challenges.

This article reflects on the potential impact of AI in higher education, from the increasing proliferation of AI tools, to the need for ethics and accountability, to the pivotal role of institutional research (IR) and institutional effectiveness (IE) offices. It begins by exploring generative AI's evolution and capabilities. It then advocates for robust ethical framework and accountability measures to mitigate AI biases. It next examines disruptive technology in academia through a historical lens. Next it discusses the need to leverage IR and IE effectiveness expertise. It concludes by embracing the role of the AI ethicist, and challenges IR/IE professionals to not only navigate the complexities of AI but also to harness its potential to shape a sustainable and inclusive future.

EVOLUTION AND CAPABILITIES OF GENERATIVE ARTIFICIAL INTELLIGENCE

Today's generative AI tools have an array of capabilities, including the ability to summarize and condense complex information, generate art and imagery, and streamline writing and research (Megahed et al., 2023). Using natural language prompts, large language models (LLMs) like ChatGPT, Google Bard, Microsoft Bing Chat, Jasper.ai, Perplexity, HuggingChat, Language Model for Dialogue Applications (LaMDA), and Large Language Model Meta AI (LLaMA) can draft sophisticated written content. Based solely on descriptive text, these models can create reports, marketing materials, cover letters, and program code. Furthermore, they can summarize dense material and provide sentiment analysis of uploaded content. Generative art tools such as Midjourney, Stable Diffusion, Leonardo AI, and Adobe Firefly have the capability to convert descriptive text into studio-quality art and imagery. Finally, AI-enhanced tools like Elicit and Consensus can accelerate the process of identifying and reviewing research studies and articles, complete with citations (Lund et al., 2023).

The landscape continues to evolve. Third-party plugins can enhance ChatGPT capabilities by providing access to external resources and services (OpenAI, 2023). Multimodal large language models (MLLMs) like Microsoft's Kosmos-2 can accommodate a broader range of input types than just text, including images, audio, and video (Peng et al., 2023). Autonomous AI agents, such as Auto-GPT and Tree of Thoughts, can be assigned an objective and can be programmed to run on an iterative loop until that objective has been met (Nakajima, 2023;

Tindle, 2023; Yao et al., 2023). In these models, intermediate steps are generated, tested, and updated without human guidance.

Research indicates that GPT-4 is performing “strikingly close to human-level” in executing tasks across a diverse range of disciplines such as law, medicine, psychology, mathematics, and programming (Bubeck et al., 2023, p. 1). In 2022, GPT-3 was nearly able to pass the U.S. Medical Licensing Exam (Jenkins & Lin, 2023; Kung et al., 2023). And in 2023 GPT-4 successfully passed the Uniform Bar Examination (Katz et al., 2023). This evolution highlights the rapid advancements in AI, marking an era of possibility for this transformative technology.

THE NEED FOR ETHICS AND ACCOUNTABILITY IN MITIGATING ARTIFICIAL INTELLIGENCE BIASES

The future is not a vague, distant concept. In discussions about technology and society, a quote by science fiction author William Gibson (2003) is frequently cited: “The future is already here—it’s just not evenly distributed.” His phrase implies a disparity where advanced technologies are available to some groups but not to others. It highlights the need to democratize technology and make its benefits more universally accessible.

Coded Bias is a 2020 documentary film directed by Shalini Kantayya that delves into the biases embedded within AI technology. The film centers around MIT media researcher Joy Buolamwini, who discovered that facial recognition systems failed to recognize her own face. This discovery led Buolamwini to investigate further how AI technology can disproportionately affect minorities (Kantayya, 2020). The film goes on to criticize how the lack of legal structures around AI results in human rights violations. It reveals how specific algorithms and AI technologies discriminate based on race and gender, affecting vital areas of life such as housing, job opportunities, health care, credit, education, and legal issues.

Following her discoveries, Buolamwini and her colleagues testified about AI before the U.S. Congress. Buolamwini then established the Algorithmic Justice League (AJL), a digital advocacy group whose goal is to address these biases and create a fair and accountable AI ecosystem by increasing awareness, equipping advocates, and uncovering AI abuses and biases (AJL, n.d.). AJL members advocate for accountability through third-party audits of AI algorithms (Koshiyama et al., 2021; Raji et al., 2023).

Fortunately, progress has been made since the documentary *Coded Bias* was released (Kantayya, 2020). In August 2022 AI resolutions were introduced in at least 17 states (National Conference of State Legislatures, 2022). In October of the same year, the White House (2022) published the “Blueprint for an AI Bill of Rights” to address potential harms. Meanwhile, the European Parliament has taken the lead in legislation safeguarding individuals from possible AI-related hazards. In June 2023 the Council of the European Union voted to approve the Artificial Intelligence Act (European Parliament and Council of the European Union, 2021), the most far-reaching legislative piece on AI. The European Union’s Artificial Intelligence Act addresses concerns about surveillance, algorithmic discrimination, and misinformation; it also introduces regulations and requirements for AI developers, which could be likened to the European Union’s General Data Protection Regulation (2018).

The future is indeed upon us but is not uniformly accessible, as evidenced by the bias in technologies like AI. The work by Joy Buolamwini and the AJL has brought this bias to the forefront. These bias-related issues underline the importance of democratizing technology by enforcing privacy, fairness, and transparency in AI tools (Cath, 2018; Mhlanga, 2023). With the increasing capabilities of AI models, the urgency for human oversight becomes ever more crucial (Prud'homme et al., 2023). While AI can accomplish remarkable feats, it is fundamentally important to acknowledge that human guidance and ethical considerations are pivotal to guaranteeing responsible and beneficial outcomes.

A HISTORY OF DISRUPTIVE TECHNOLOGY IN ACADEMIA: A MULTIDISCIPLINARY APPROACH TO GOVERNANCE

AI is not academia's first encounter with disruptive technology. One only needs to look to the recent past to see similar concerns and debates around the use of the Internet, analytics, mobile technology, data science, and cloud computing. Addressing the impact of these technologies required a multidisciplinary approach involving higher education professionals from across the academy. The same approach can be used for generative AI.

Gasser and Almeida (2017) addressed how governance mechanisms, accountability, and transparency can be jointly examined with broad stakeholders when dealing with technological black boxes. Mirroring a model used for the General Data Protection Regulation, the authors proposed a three-layered framework for regulating AI systems, covering its technical, ethical, and legal aspects. These layers offered a broad but practical approach to implementing governance structures for AI, an approach that can vary among industries and organizations.

Officials in higher education institutions can use a similar multipronged approach. Colleagues in multiple divisions can work both independently and in concert to tackle AI issues. University information technology offices can address AI from a technical perspective by managing how physical and software systems interact with AI algorithms. This layer can focus on transparency, audits, algorithmic accountability, and fairness in data usage. Likewise, the general counsel, compliance, and human resources offices can address AI from a regulatory and policy perspective. This layer can incorporate technical and ethical insights into legal and regulatory frameworks (Viljanen & Parviainen, 2022). Finally, IR and IE officers can approach AI from an ethical perspective through oversight, evaluation, policy development, and data governance.

Given the speed of advancements, even full-time AI researchers report feeling anxious and overwhelmed (Togelius & Yannakakis, 2023). The difficulty for educational professionals is further exacerbated by the traditionally glacial pace of educational transformation. However, established principles and frameworks can be a consistent foundation for navigating the evolving technological landscape (Taeihagh, 2021).

LEADING THE CHARGE: LEVERAGING INSTITUTIONAL RESEARCH AND INSTITUTIONAL EFFECTIVENESS EXPERTISE

IR/IE offices are tasked with collecting, analyzing, and using data to support decision-making, planning, policymaking, and institutional improvement. Moreover, it is a fundamental aspect of the IR/IE professionals' role to establish robust engagement, encourage collaboration, and ensure open communication with stakeholders across their respective institutions. As custodians and advisors of data-informed decision-making, IR/IE professionals provide crucial context and nuance to their organizations. As such, IR/IE professionals are frequently entrusted to lead and advise on projects related to data literacy, data governance, and institutional assessment. Leadership in implementing AI strategies is not such a far reach. The skillset, relationships, and experience required to excel in their current roles can help IR/IE professionals navigate this era of technological change. The ability to interpret data and communicate insights effectively is essential to AI development and implementation.

The remainder of this article outlines how IR/IE professionals can take an active role in leveraging AI for their institutions. Some suggestions may seem aspirational, given that many IR/IE offices frequently work under high demands and with scarce resources. However, strategies that are applied incrementally can still lead to impactful changes despite resource limitations. AI can benefit small IR/IE offices by enhancing workflow to create more capacity. The time saved by leveraging AI individually can then be redirected toward leveraging AI organizationally.

EMBRACING THE ROLE OF ARTIFICIAL INTELLIGENCE ETHICIST: GUIDELINES FOR INSTITUTIONAL RESEARCHERS AND INSTITUTIONAL EFFECTIVENESS PROFESSIONALS

One crucial role that IR/IE professionals can play is that of AI ethicist. Niederman and Baker (2023) argued that the ethical issues associated with AI are not unique, and current frameworks have the capacity to tackle them. In their study, Jobin et al. (2019) conducted an extensive analysis of 84 AI ethics reports that had been drawn from a diverse range of private corporations, research institutions, and governmental bodies. Through a thematic analysis, they discovered an agreement across these reports, centering around five key ethical considerations for AI: transparency, fairness, safety, accountability, and privacy. To guide their actions, IR/IE professionals can look to the Association for Institutional Research (AIR) Statement of Ethical Principles (AIR, 2019) as their North Star. The statement equips IR/IE professionals with a flexible and familiar framework to effectively handle the concerns and complexities associated with AI. It comprehensively addresses a multitude of concerns that have been raised by those expressing apprehension about AI. Like the above ethical considerations, the AIR statement emphasizes privacy, accuracy, contextual relevance, fairness, transparency, and accessibility. These principles can serve as a compass to guide practitioners in their work with AI as the AIR statement has successfully done with the tools and technologies that preceded it. Following are a few suggestions on how IR/IE professionals can apply these ethical principles.

Continuous Learning and Development

A good guide must understand the terrain. The first step in leveraging AI involves taking time to understand and experiment with it. As with any new skill, proficiency will develop through practice and application. Fortunately, gaining AI expertise is no longer a steep hill to climb.

Many LLMs, such as ChatGPT, Google Bard, Claude, and Microsoft Bing Chat, are free and accessible. Despite some models being proprietary, the information about the technology and its foundational principles are documented and available. The only differences among models lie in the specific data sets on which they are trained—which can vary significantly. Traditional ML models often rely on supervised learning, where the model is trained on data sets that are known. LLMs, on the other hand, use unsupervised learning techniques on vast amounts of data in order to train models to predict the next likely word in a phrase or sentence. Given the sheer enormity and complexity of these models, LLMs are effectively black boxes designed to generate human-like responses. Knowing this, IR/IE practitioners should focus on applying LLMs to areas where their strengths can be used most effectively.

From a practical standpoint, there is no shortage of documentation, videos, forums, and communities to obtain tips, techniques, and examples. The act of designing, testing, and refining AI instructions is called "prompt engineering." The process is similar to developing effective research questions. It requires an understanding of context and a willingness to continue refining. Arming oneself with technical and practical information will go a long way toward reducing anxiety and increasing competence. Once competence is attained, education of the community and leveraging of AI can occur.

A black box model is not a substitute for the skills, expertise, transparency, and nuanced judgment an experienced IR/IE professional can provide. Thus, an IR/IE professional's responsibility must extend beyond just describing these models to stakeholders. It is crucial to educate users about their underlying methodology and limitations. Practitioners can offer clarity and insight to campus community members, and can equip them with knowledge of these models' capabilities and limitations. This understanding can empower stakeholders to make informed decisions about the use of AI.

Ethical Deployment

The significance of ethics in AI usage, even when using publicly available tools, cannot be overstated. Upholding ethical principles is essential at all stages of AI adoption, from selecting the right tool, to understanding data needs, to deployment of AI in daily operations. Collaboration across institutional teams is crucial to maintaining these ethical standards. IR/IE professionals can foster interdepartmental cooperation, thus ensuring that AI tools are used responsibly and ethically, in line with the best interests of campus stakeholders. Soliciting campus feedback can broaden and diversify perspectives on AI tool use. Facilitating open dialogues on AI ethics can stimulate ethical mindfulness. Finally, establishing training sessions on AI ethics can strengthen awareness and responsible usage.

Privacy and Confidentiality

When using generative AI tools, IR/IE professionals can establish privacy and confidentiality by first understanding existing tools and their privacy policies. IR/IE professionals can then adapt a range of established research protocols to protect user data further and to limit exposure. These protocols include practices like data minimization, where only the necessary data are input into the AI tool. This technique reduces the risk of privacy breaches. Another approach would be to anonymize any personal data before they are input into the tool. A third protocol would be to obtain informed consent when sensitive data are used, even when personal identifiers are removed. Furthermore, educating staff on privacy and responsible AI use is essential. Finally, one should not hesitate to consult with legal counsel to ascertain that all necessary precautions are being taken.

Bias and Fairness

IR/IE professionals know that bias can be introduced at multiple stages of the research process and must be managed (Roulston & Shelton, 2015). Likewise, bias can be inserted at multiple points in AI models and must be mitigated. Bias can be hidden in the training data, algorithms, and the subjective choices of their creators. In her TED Talk, Cathy O'Neil (2017) challenged the common perception that algorithms were objective, and asserted that algorithms were influenced by the biases of their designers. The same protocols to mitigate bias in research can also be applied to AI use.

IR/IE offices can adopt several measures to minimize bias and enhance fairness when using publicly available generative AI tools. One of the first steps is to carefully review and select the tools to be used. It is essential to choose tools with a reputation for fairness and transparency. The selection process can include reading reviews and studying case studies to make an informed choice. Once the right tools have been chosen, it must be understood that the process can still be contaminated with biased input data. Practitioners must ensure that the data fed into these models fully represent the populations and scenarios to be considered. Additionally, practitioners must use professional judgment when interpreting and presenting results. Involving key stakeholders at each stage can help ensure that diverse perspectives are considered.

Accountability and Responsibility

Working collaboratively with campus colleagues, IR/IE professionals can help drive the discussion on AI accountability. These dialogues should not be theoretical but rather should be grounded in specific use cases. They must identify who will take responsibility when an AI system inflicts harm or commits a significant error (Dignum, 2018). For example, someone must be willing to take responsibility if an AI tool is used to make an incorrect prediction that impacts a student negatively. Comfort in taking responsibility will require proficiency with the AI tools used, the establishment of clear guidelines for usage, and clear communication with other stakeholders. IR/IE professionals can facilitate all of these steps.

Furthermore, a review mechanism and an appeal process should be established to evaluate decisions informed by AI. Finally, a strategy to ensure accountability is to include third-party audits. External evaluators bring an objective perspective and use distinct methodologies and frameworks for assessment. These auditors serve as a safeguard, adding another layer of scrutiny to AI usage and decision-making processes.

Transparent and Explainable Artificial Intelligence

Transparency is necessary for developing trust among student, administrative, and faculty stakeholders. Furthermore, transparency is a fundamental principle that underpins robust and credible research. Extending this principle to AI is relevant and necessary. IR/IE professionals can champion the need for transparent and explainable AI. It is difficult to achieve transparency when dealing with something that is continually evolving. Examining the issue from a legal perspective, Miriam Buiten (2019) acknowledged this difficulty and proposed a practical solution: instead of creating new regulations for a rapidly changing field, Buiten recommended the application of existing regulations from a more familiar but related area. Likewise, IR/IE practitioners can follow a similar strategy by applying the established principles of good research design to AI use. One does not need to be an AI expert to ensure transparency. IR/IE professionals can uphold the principle of transparency by assisting with tool selection, researching methodology, maintaining open communication with the community, and being an example of ethical and responsible use.

Student Involvement and Communication

As discussed by Emily Oakes, Yih Tsao, and Victor Borden in their article in this volume, it is critical to incorporate the student voice in the work of student success. Student voice refers to individual students' and student groups' values, beliefs, perspectives, and cultural backgrounds. Higher education professionals must listen to, learn from, and respond to the collective student voice. Unfortunately, a recent meta-analysis of media articles on AI's impact on higher education found little mention of the student voice (Sullivan et al., 2023). Instead, the dominant discussion focused on institutional concerns about academic integrity. This oversight must be corrected. Together with their peers in student affairs, IR/IE practitioners with qualitative research backgrounds can help lead the discussion. Involving and communicating with students about AI tools that affect them is crucial. It is important to seek methods to educate students about these AI tools involved in their education, emphasizing their rights, benefits, and potential risks.

Develop Institutional Policies for Artificial Intelligence

Finally, having articulated policies and procedures can help guide the campus community toward responsible AI use. I agree with Webber and Zheng (2020) that change is best facilitated through campus-wide strategies. This guiding strategy should include rules for data collection and usage, principles establishing AI transparency, directives for setting data use parameters, processes for initiating the ethical review of AI tools, and mechanisms for ensuring accountability across one's campus or organization. Such policies would not only uphold institutional integrity but also enhance the effectiveness and value of AI in supporting data-informed decisions and optimizing institutional outcomes.

CONCLUSION

AI will be increasingly impossible to ignore. Microsoft, Google, Adobe, and other architects of the digital ecosystem have already begun to embed AI into their existing applications (Microsoft, 2023). Being a passive spectator is neither optional nor tenable. Fortunately, the frameworks and skillsets that have enabled IR/IE professionals to thrive in their current roles can empower them to transition from mere observers to key influencers during this technological revolution.

It is essential to remember that the tools now considered indispensable to IR/IE professionals were once enigmatic and unfamiliar. The same strategies used to master data visualization, business intelligence, statistical analysis, and data science can be used to leverage AI. Armed with research expertise, ethical commitment, data-informed decision-making knowledge, and a profound belief in human insight, IR/IE professionals stand ready to both adapt and lead. By harnessing this unique combination of skills and perspectives, IR/IE professionals can confidently step into the future and remain valued leaders in the higher education community.

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