The AIR Professional File

Fall 2023 Volume

Supporting quality data and decisions for higher education.

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

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PREFACE

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

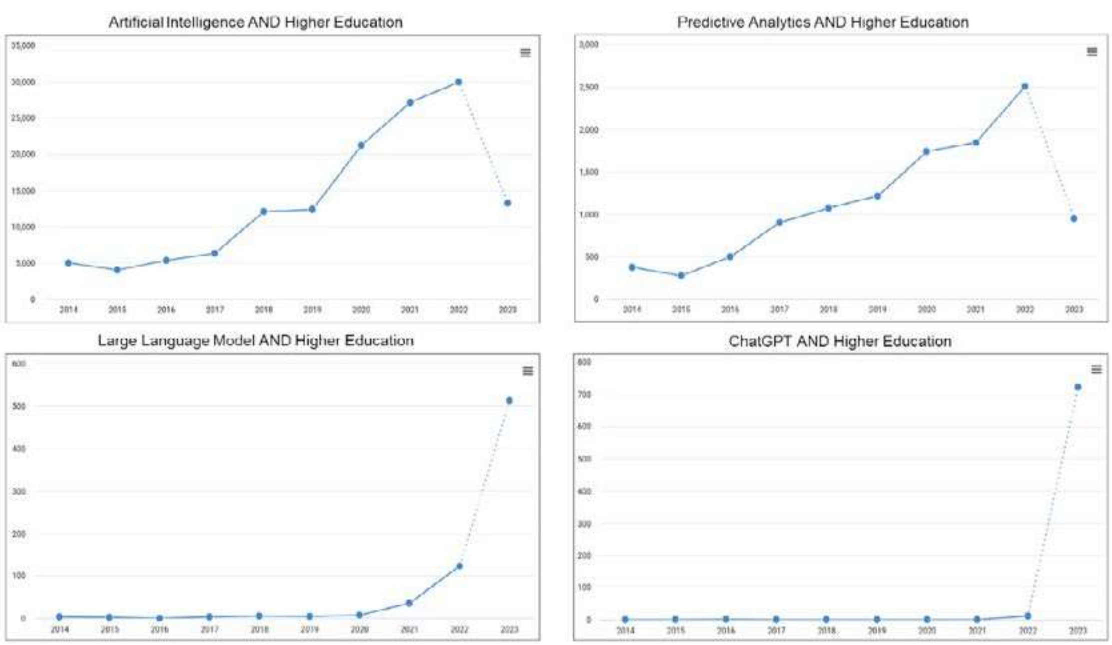
New technologies in our post-pandemic world have prompted substantial changes in every facet of higher education. The emergence of Big Data is one of several key facilitating conditions that accelerated the adoption of artificial intelligence (AI) and machine learning (ML) in key application areas. According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

Henry Zheng
Karen Webber

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

Randhir Rawatlal and Rubby Dhunpath

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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).

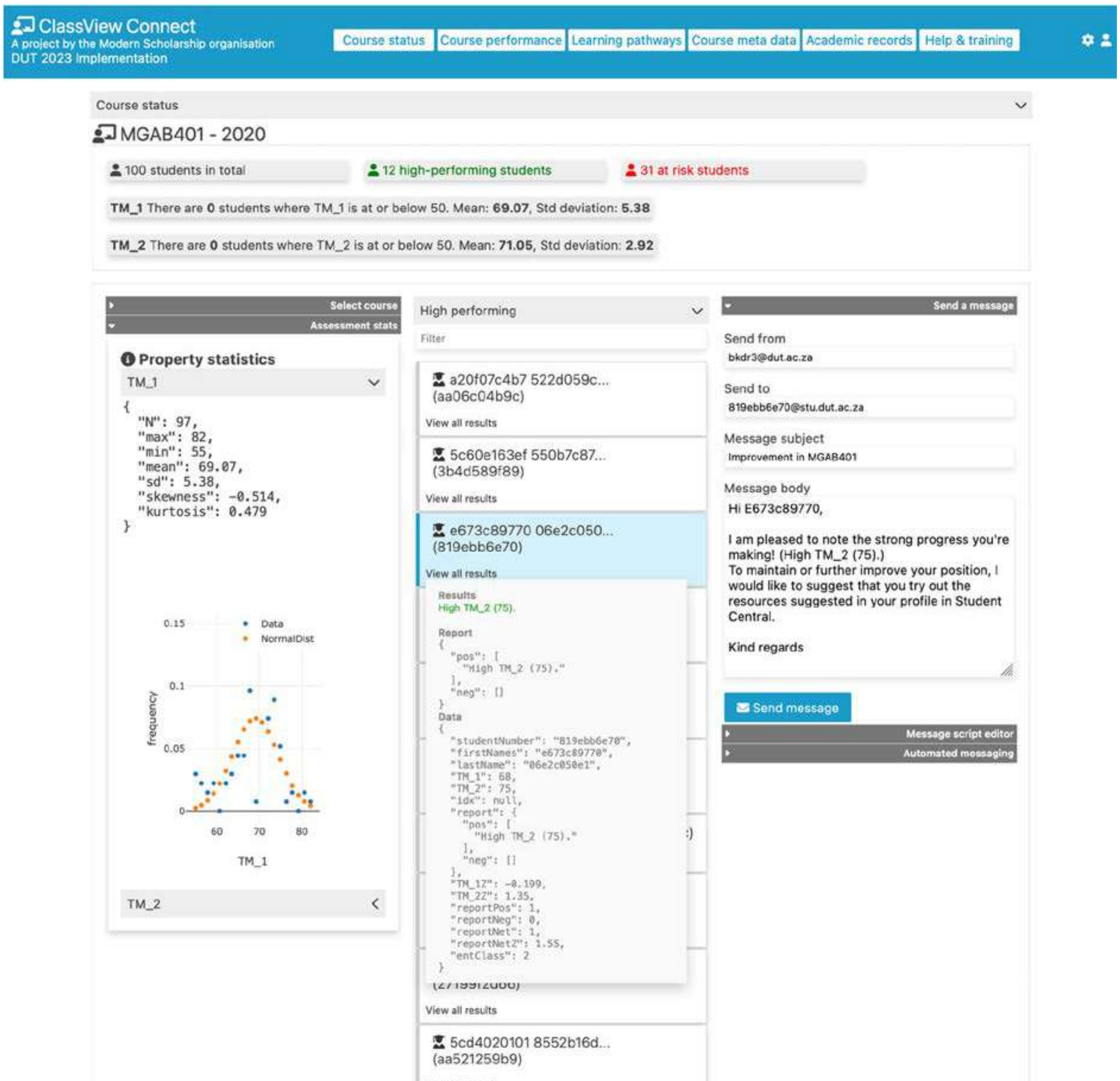
At Georgia State University (GSU), a chatbot helps students with preenrollment processes such as navigating financial aid (Nurshatayeva et al., 2021); GSU’s chatbot has led to significant increases in retention and graduation rates. The chatbot’s effectiveness continues after enrollment: research indicates 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.

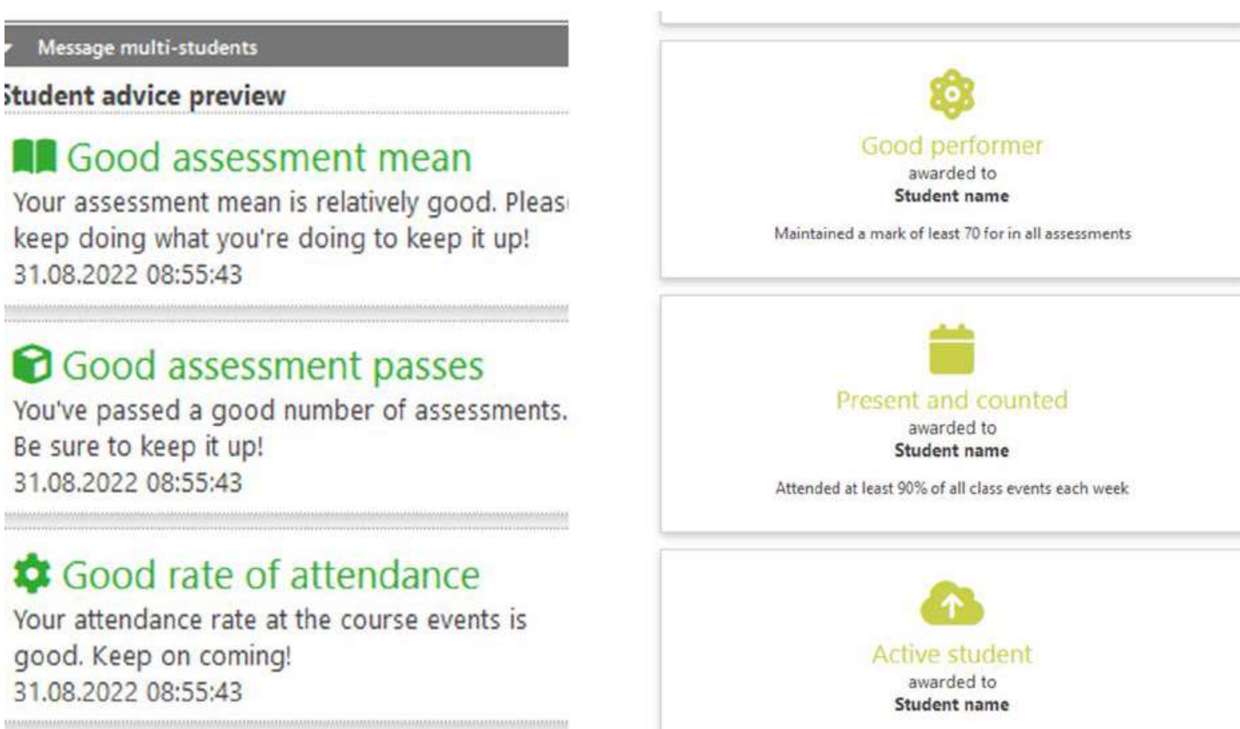


Note: Student numbers and names have been hashed.

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.

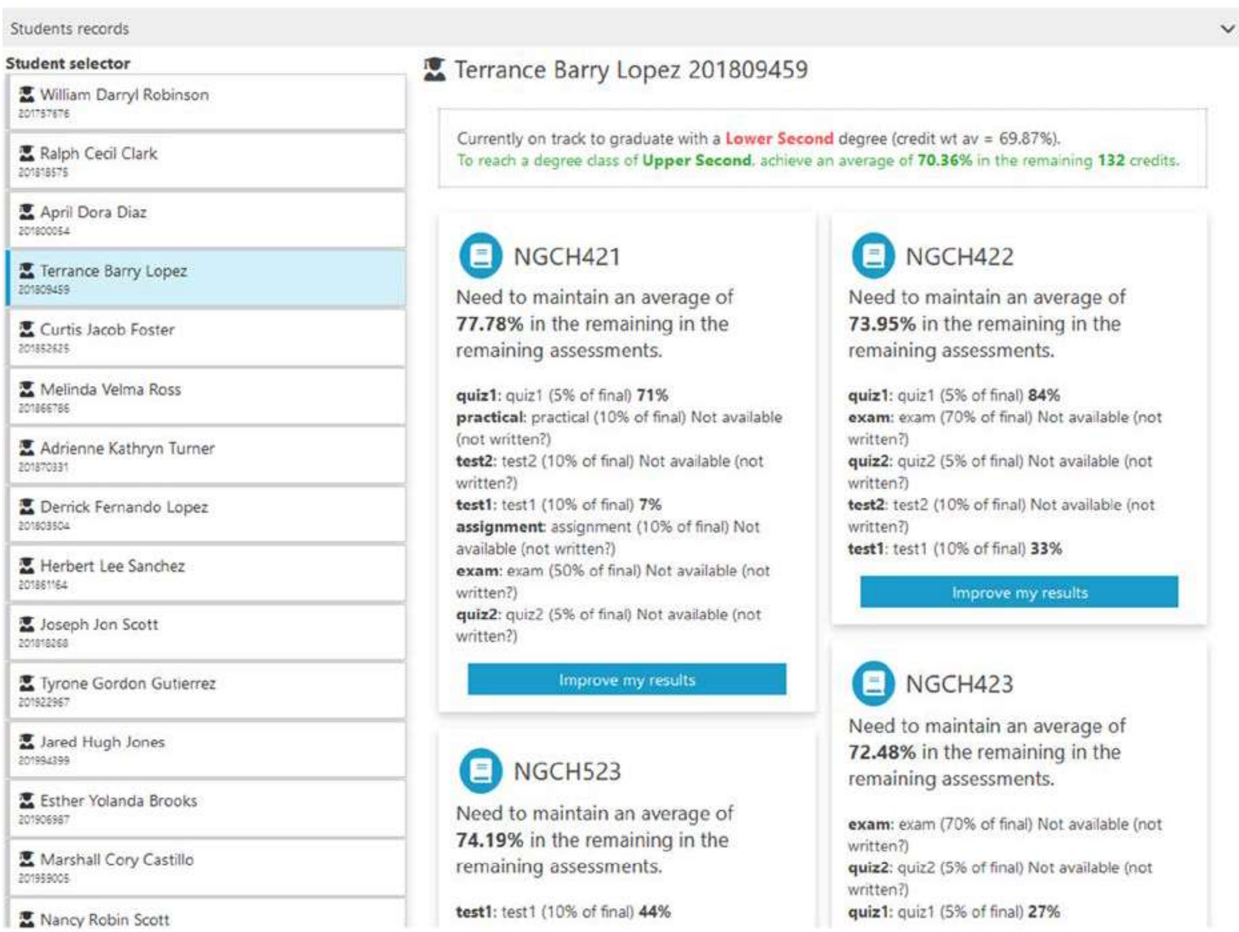
The advising concept may be further generalized to include gamification elements. As shown in Figure 2, the advising may take the form of virtual awards and badges that can be attached to a student's profile. Although these virtual awards require no resources from the institution, they are a powerful 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

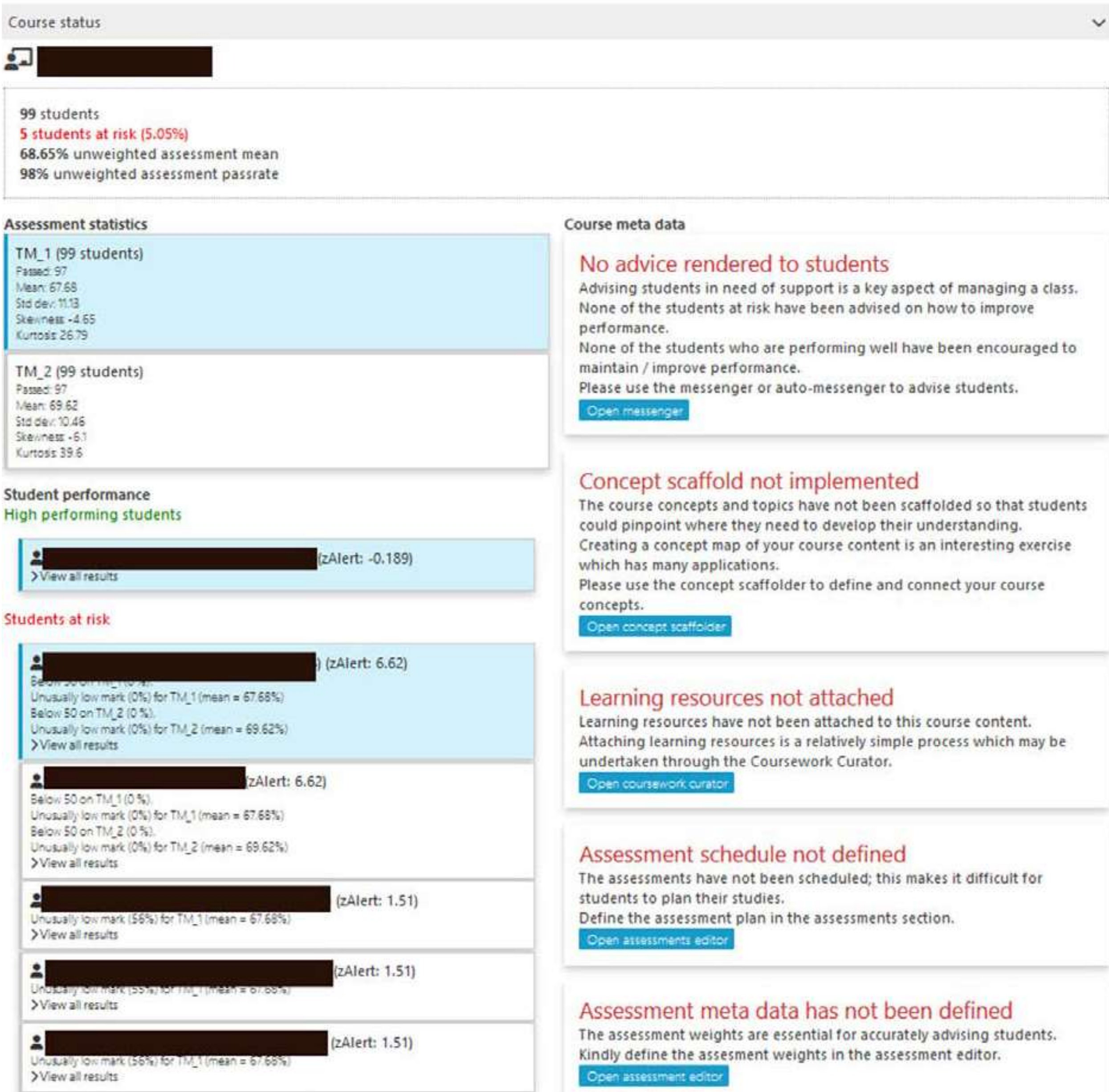
To achieve significant improvements in the progression and hence the graduation rates, it is necessary for the various role players to receive accurate advice. At the student scale, advice on coursework registration as well as day-to-day study habits are a direct influence. Advice to lecturers with respect 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



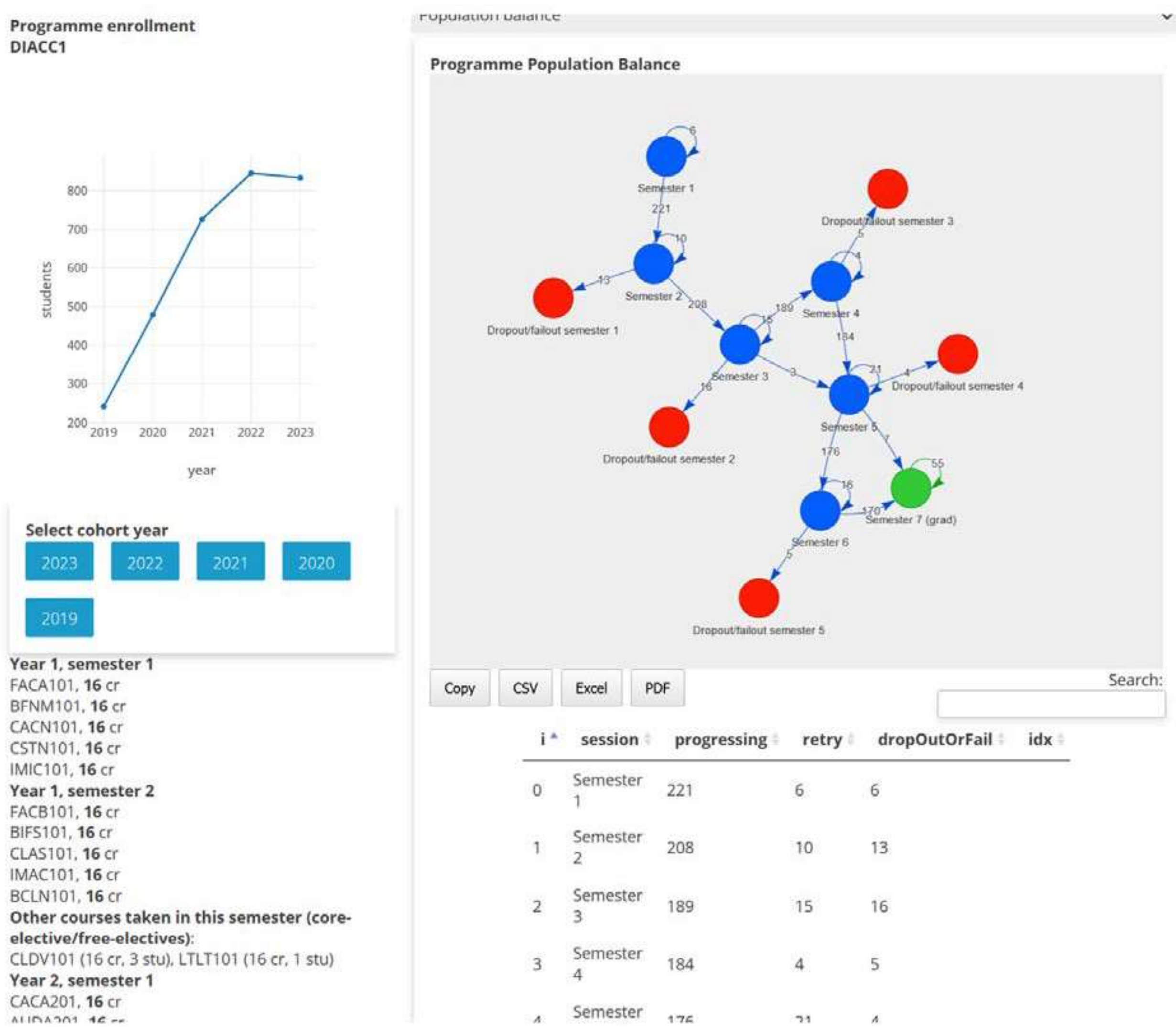
Note: Advice rendered to lecturers to manage classes better.

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

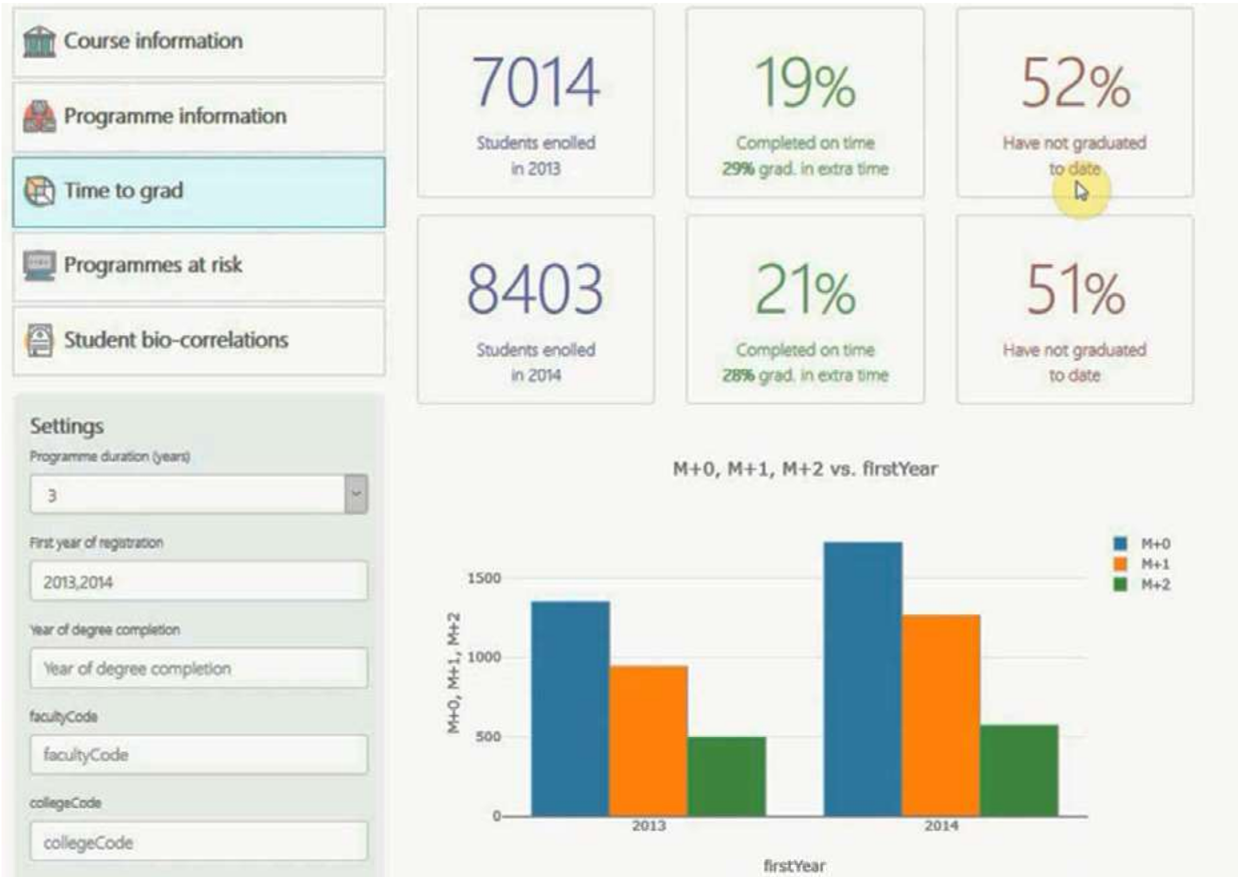
To fully advise faculty staff on student progression, it is also necessary to evaluate the transfer of students from one semester to the next, and to maintain awareness of the various combinations of courses involved in the various routes to graduation. Figure 6 illustrates that a program manage can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



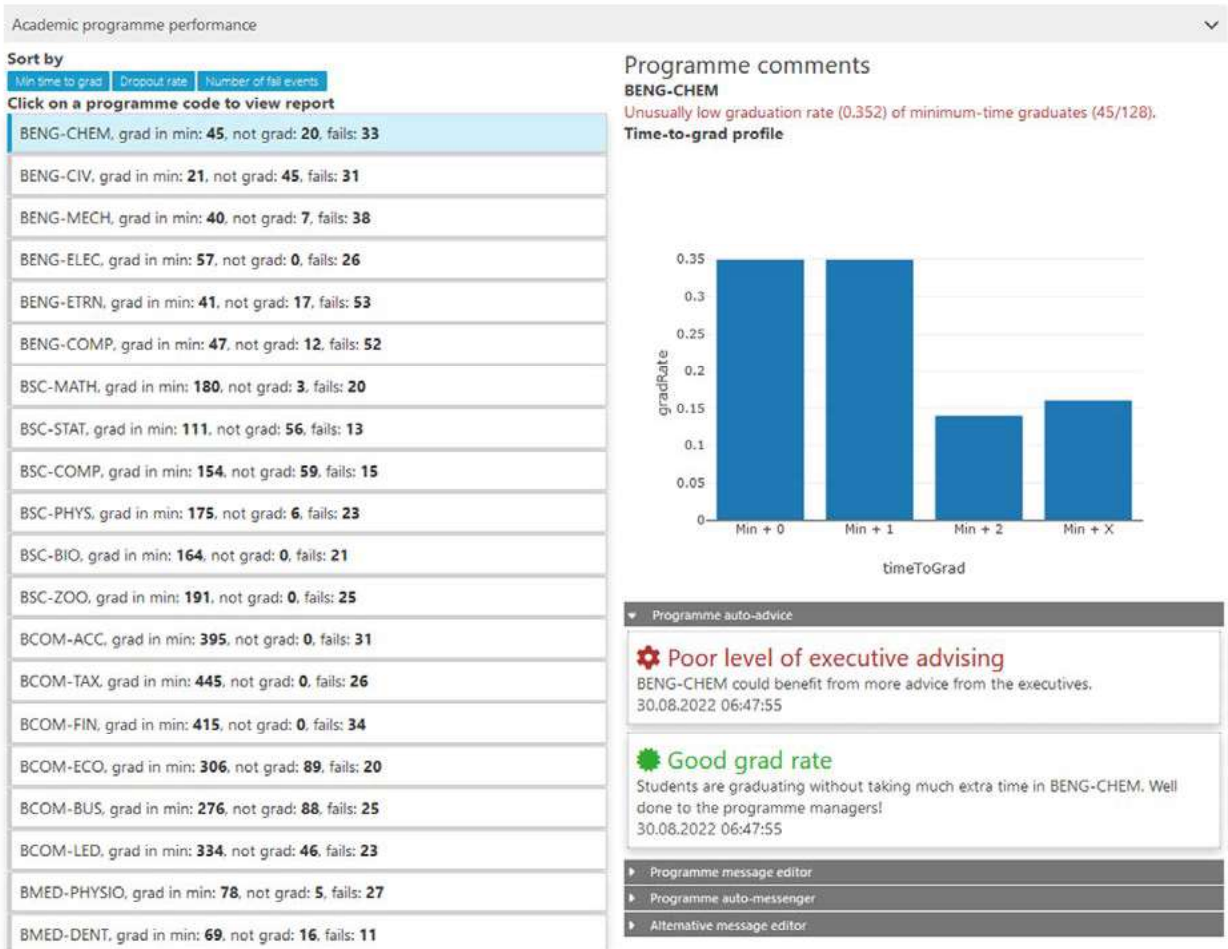
At the whole-institution scale, executives maintain a bird's-eye view of the entry and graduation statistics. In particular, given an entering cohort in a particular year, it is necessary to monitor what fraction of students complete in minimum time and what fraction exit without graduating (Figure 7).

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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